

ESSAYS ON CLIMATE, HEALTH AND ECONOMICS

By

ANTOINETTE MUJINGA MASHINDA

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SUPERVISOR: PROFESSOR STEVEN F. KOCH

ABSTRACT

The impacts of climate change are predicted to continue worsening and developing countries are expected to bear the hardest burden. Extreme temperatures or precipitations, wildfires, floods, and droughts contribute to increasing health problems, leading to adverse impacts on cognitive development, employment, and earnings. Despite the increasing evidence of the link between climate and health, this has yet to be fully explored in developing countries. Thus, this thesis aims to deepen the understanding of the relationship between climate, health, and economics in Africa.

Linking Demographic and Health Surveys (DHS) with climate data, the thesis investigates the long term impact of droughts on women's health and socioeconomic outcomes as well as on the health of their children. The findings indicate that exposure to cumulative droughts during childhood is associated with lower educational attainment and household wealth in adulthood, increased probabilities of having underweight and low birthweight offspring, and a higher likelihood of giving birth to female children. The thesis also finds that the long term effects of droughts are mainly felt by boys than girls.

The thesis further explores the remediating role of positive rainfall shocks on catch-up growth in weight for low birth weight (LBW) children in Kenya. Using the relative and absolute definitions of catch-up growth expressed as a positive change in either WAZ or Weight for Age Difference (WAD), respectively, the paper finds that LBW children experience catch-up growth in weight both at ages 2 and 4 and that positive rainfall shocks, specifically moderate moisture, may improve both WAZ and WAD, serving as a remedial investment.

Finally, the thesis uses anonymised daily Covid-19 case data and Meteorological data to explore the impact of temperature and relative humidity on the incidence of Covid-19 in Cape Town while distinguishing between Low and High socio-economic status (LSE, HSE) areas. Using the distributed-lag nonlinear model (DLNM), the findings show that people from HSE were more vulnerable to cold effects than those from LSE. Heat effects significantly lowered the risk of Covid-19 incidence in LSE; in contrast, heat effects increased the risk in HSE. Relative humidity increased the risk of Covid-19 in all areas.

Dedication

This Thesis is dedicated to The Almighty God

Declaration

I, Antoinette Mujinga Mashinda, declare that this research is entirely my own and where necessary due credit has been given. This thesis is submitted in fulfillment of the requirements for the degree of Doctor of Philosophy at the University of Pretoria. It has not been submitted before for any degree or examination at any other university.

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1 CHAPTER 1 Introduction

1.1 Backdrop

The fate of humanity has been closely tied to changes in climate, encompassing both short-term fluctuations and long-term shifts occurring over centuries or even millennia. They are thought to have influenced and potentially spurred the initial cultivation and domestication of crops, as well as the domestication and herding of animals. Human societies have continually adapted in response to these climate variations (Jackson 2024). Climate change encompasses a range of phenomena, from rising temperatures to alterations in precipitation, and an increase in the frequency and severity of extreme weather events. Year after year, weather and climate-related disasters contribute to an increased burden of disease and mortality (Di Napoli et al. 2022). The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2023) warns that the harmful impacts of climate change will continue to worsen. The report further indicates that developing countries, although they contribute the least to global emission, bear the largest burden arising from climate change. There is an expected 15 times increase in death from extreme weather events, compared to developed countries.

Climate change affects human health through both direct and indirect pathways, with subsequent repercussions (Boumans et al. 2014). Direct pathways stem from extreme temperatures or precipitation. Extreme temperatures can lead to heat-related illnesses, such as heatstroke and heat exhaustion. High temperatures also increase the risk of wildfires, which can affect air quality and exacerbate respiratory issues like asthma and other lung diseases. Changes in precipitation patterns lead to floods and droughts, increasing the spread of vector-borne diseases, such as malaria and dengue fever. These diseases are spread by disease-carrying vectors, such as mosquitoes and ticks, the distribution and behavior of which are influenced by warmer temperatures (Di Napoli et al. 2022). For instance Ro-

manello et al. (2021) observe that the period of time with environmentally suitable conditions for the *Plasmodium Falcifarum* malaria increased by 39% in 2010-2019, compared to 1950-1959; the same trend is observed for the pathogen responsible for Cholera, which causes an estimated 100 000 deaths per year.

Furthermore, climate change can indirectly affect health in several ways. Changes in rainfall patterns can lead to water scarcity, increasing the risk of malnutrition due to reduced food production and waterborne diseases. Also, climate change can lead to more frequent and intense natural disasters, which can disrupt healthcare systems and lead to physical and mental health issues. In addition, economic disruptions that occur after a disaster in weather-sensitive industries, like agriculture, tourism, and fisheries, can indirectly impact health. Some effects include increased stress, anxiety, depression, and other mental health issues, due to the loss of livelihoods (Marazziti et al. 2021; Romanello et al. 2021).

However, the health impacts of climate change on individuals is dependent on factors, such as: age, gender, economic status, and the availability of health infrastructure and systems. In particular, children, pregnant women and the elderly in developing countries may be especially vulnerable to climate change (Patz and Thomson 2018). Several studies find a link between weather- or climate-related disasters and health, particularly for children and women. Higher temperatures increase child undernutrition (Randell, Gray, and Grace 2020; Baker and Anttila-Hughes 2020), while pregnant women are vulnerable to heat waves (Deschênes, Greenstone, and Guryan 2009; Y. Zhang, Yu, and Wang 2017; Ebi et al. 2021). Moreover, rising temperatures and increasingly frequent droughts affect agricultural food systems and water availability, while floods also increase runoff. Thus, water bodies may become unsafe, due to pollutants and toxic elements that elevate the risks of hepatitis and sepsis in pregnant women (Ahmed, Zounemat-Kermani, and Scholz 2020). In addition, in developing countries, the burden of water collection overwhelmingly falls on women; hence, water insecurity means that women spend even more time collecting and transporting water, which may result in injuries, arthritic diseases and mental health issues (Abid et al.

2018; Geere and Hunter 2020).

Despite the increasing evidence of this link, the impact of climate change on health has not been fully explored (Azam and Awan 2022). Previous research focused on developed countries, mainly due to data limitations in developing countries. However, with the emergence of new data sources, researchers are now able to bridge this gap and explore the link between weather-related shocks and health outcomes (Currie and Vogl 2013). Therefore, it is necessary to further explore the association between climate and health (Ye et al. 2001; Azam and Awan 2022). Such research is important in Africa, because health is crucial for economic development and prosperity, due to its relationship to labour market outcomes and productivity. Moreover, health is part of human capital formation, together with education (Azam and Awan 2022; Doan, Strazdins, and Leach 2020). For instance, the impact of environmental conditions on early childhood undernutrition have been found to cause structural damage to the brain and impair motor development in infants, which affects the child's cognitive development (Black, Trude, and Lutter 2020). It can lead to further issues in adulthood, influencing educational attainment, employment prospects, and earnings (Almond, Chay, and Lee 2005; Almond and Currie 2011; Currie and Vogl 2013; Cutland et al. 2017; Bougma et al. 2022; Weldesenbet 2022). In addition, the socioeconomic disparities associated with environmental conditions can further aggravate susceptibility to poor health, perpetuating cycles of poverty in subsequent generations. Thus, this thesis aims at deepening the understanding of the link between climate, health and economics in the context of developing countries, namely Kenya and South Africa.

Kenya is a good case study for the analysis. Over 80% of the country's land is classified as Arid and Semi-Arid Land (ASAL) with drought as the most common natural occurrence. The risks from persistent droughts have increased, with Northern Kenya alone experiencing 28 major droughts over the past 100 years; these have been at increasingly frequent intervals, with three occurring in the last decade. The severity and frequency of droughts in the country appears to be increasing over time (Ndegwa and Kinyua 2018). This trend

is likely to continue or worsen (Distefano and Kelly 2017; IPCC 2021), resulting in water availability and accessibility that is highly variable, spatially and temporally, presenting constraints to production. In this context, rainfall shocks offer an opportunity to explore the relationship between health and climate.

To broaden the scope of this analysis beyond rainfall, South Africa provides a complementary case to explore how socioeconomic disparities related to environmental conditions affects, or at least correlates with, the spread of infectious diseases, like COVID-19. With one of the highest Gini coefficients globally, South Africa offers insight into how structural disparities linked to access to resources, and services influence public health outcomes. Specifically, Cape Town, the country's second most populous city, is an urban center in the global South, in which social and spatial segregation is prevalent. Inequalities are also visible in access to public infrastructure and services. The population is concentrated in sub-districts and areas, often reflecting their socioeconomic and cultural differences. We use this spatial variation to examine the relationship between weather and COVID cases.

For the Kenyan component of the analysis, we link data from the Demographic and Health Surveys, accessed through Integrated Public Use Microdata Series database – IPUMS-DHS (Boyle, King, and Sobek 2024)– and climate data from the renowned Climate Research Unit's Time-Series, CRUTS (Harris et al. 2014, 2020). With this data, the thesis investigates the long-term impacts of rainfall fluctuations on women in rural households and the potential intergenerational transmission of these effects to their children aged 0 - 59 months. We further explore the opposite possibility, that positive rainfall shocks could help low birth weight children 'catch-up' to normal birth weight children. We use cumulative rainfall measures of distinct natural experiments to identify the impact of early life shocks in different regions and years. This research also considers socioeconomic status as a potential mediator through which climate affects intergenerational health.

For the remainder of the thesis, we use anonymised daily COVID-19 case data obtained

from the Western Cape province COVID-19 dashboard. The data was publicly accessible for the period covering 1 March 2020 to 24 January 2021. We combine this with meteorological data collected from the South African Weather Service (SAWS), focusing on the seven monitoring sites in the City of Cape Town. The combined data is used to explore the association between climate and the incidence of COVID-19 in Cape Town, while distinguishing between low and high socio-economic status sub-districts.

Hence, the thesis attempts to answer three questions. First, what are the long-term impacts of drought on women, and could these impacts be transmitted to their children? Second, can positive rainfall shocks mitigate or even reverse the adverse health effects for low birth weight children? Third, what is the relationship between meteorological and socioeconomic factors in the transmission of COVID-19? Below, we offer additional motivation, briefly describing the contributions to the literature. We do so for each of the research chapters in this thesis – the three that separately address the previously listed questions.

1.2 Water Scarcity and Intergenerational Transmission of Health Inequality

Climate change is predicted to exacerbate water scarcity even further through declines in precipitation and increases in evapotranspiration rates. Hydrological cycles are predicted to undergo extensive changes, cause global shifts in precipitation patterns, and increase the frequency and severity of extreme events (Distefano and Kelly 2017). Water scarcity has several short-term and long-term welfare consequences. Precipitation deficits impact food systems and reduce agricultural production and nutrient intake, impacting health outcomes (Carpena 2019; Amondo, Nshakira-Rukundo, and Mirzabaev 2023). Moreover, it can affect the prevalence of vector-borne diseases, waterborne and water-washed diseases, such as diarrhea, malaria, and dengue fever, which particularly affect young child health through undernutrition. Bhutta, Aimone, and Akhtar (2019) estimate that children bear more than

half of the disease burden from climate change and variability. According to the United Nations, by 2050, the number of people living in areas with severely stressed water will increase to 3.2 billion (United Nations Convention to Combat Desertification 2022).

Climate variability is increasingly recognised as a global health concern, with children being particularly vulnerable to its impacts- especially undernutrition. Inadequate nutrient intake in early life can lead to severe health risks, including impaired brain development, stunted growth, and higher susceptibility to chronic illnesses such as diabetes and cardiovascular disease (Black, Trude, and Lutter 2020; Sudiyah and Rosida 2021; UNICEF / WHO / World Bank Group 2023).

Emerging evidence shows that the consequences of early-life undernutrition can extend into adulthood, affecting educational attainment, labor market outcomes, wealth and overall well-being (Almond, Chay, and Lee 2005; Maccini and Yang 2009; Currie and Vogl 2013; Dinkelman 2017; Bougma et al. 2022). These early disadvantages may also be transmitted across generations, contributing to persistent cycles of poverty and poor health (Aizer 2017; Hyland and Russ 2019). Thus, understanding the long-term impact of climate and weather on later life outcomes is crucial, as environmental shocks experienced during childhood can hinder individual development, with negative effects that can ripple through communities, countries, and even future generations.

Recent years have seen a rise in studies examining the relationship between weather variability and several outcomes (Maccini and Yang 2009; Rabassa, Skoufias, and Jacoby 2014; Hyland and Russ 2019; Randell, Gray, and Grace 2020; Grace et al. 2021; Yamashita and Trinh 2022; Abiona 2024). However, this literature has mainly focused on the first generation impacts with less analysis of whether these effects are transmissible across subsequent generations (Tan, Zhang, and Zhang 2025). This chapter fills in the gap by studying the intergenerational effects of maternal early-life drought exposure on offspring health.

To examine aggregate rainfall effects on mothers and investigate the potential transmis-

sion to next generation, we first construct cumulative measures of drought exposure in the mother's earliest life, aligning with the approaches of (Dinkelman 2017; Hyland and Russ 2019). Cumulative drought measures allow us to consider distinct natural experiments, possibly identifying different impacts of early life shocks in different regions and years. This approach helps mitigate concerns about confounding shocks that may influence our findings on the correlation between child health and a single weather event. Using this strategy provides a robust framework for analysing the adverse effects of droughts on women's socioeconomic (wealth and education) and health (weight and BMI) outcomes that are both comprehensive and reliable (Dinkelman 2017; Hyland and Russ 2019). Since drought events are quasi-random within and across districts on a year-to-year basis, we can compare the health of children born in districts affected by drought with those born in non-affected districts across different birth years (Maccini and Yang 2009; Rocha and Soares 2015). We then test whether there is an intergenerational impact of early-life drought. We focus on a wide range of outcomes including the likelihood of having a child who is underweight, wasted and has low birth weight. We further analyse these effects by gender to explore whether drought effects differ between boys and girls.

On the other hand, there remains insufficient understanding of the pathways linking long-term effects of climate and weather to child health, because they are complex (Phalkey et al. 2015; Dasgupta and Robinson 2023). Some studies have attempted to investigate these mechanisms (Galler and Rabinowitz 2014; Straight et al. 2022; Moog et al. 2022; Racine et al. 2023) and show that the intergenerational transmission of health involves complex biological, epigenetic, environmental, socioeconomic and behavioural mechanisms. Thus, we also attempt to unpack the pathways between long-term weather conditions and offspring health, particularly for rural households. Although it is not always possible to directly test these mechanisms, due to data limitations (Phalkey et al. 2015; Randell, Gray, and Grace 2020), we attempt to estimate the mediation effect of socioeconomic status (SES) captured by two variables – wealth index and years of schooling – using a simple mediation analysis

(path analysis).

In our view, this chapter makes three significant contributions to the existing literature. Firstly, it adds to the growing body of research linking extreme weather events and health, including studies by Maccini and Yang (2009), Hyland and Russ (2019), Randell, Gray, and Grace (2020), Thiede and Strube (2020) and Dasgupta and Robinson (2023). Our specific focus on both adult outcomes and childhood health allows us to expand upon previous research and shed light on how drought exposure during early years impacts long-term socioeconomic status and subsequently child health. Secondly, we examine a range of weather shock periods and durations. We examine the effects of rainfall deficits during early life up to 4 years old, as well as the *in utero* period, focusing on cumulative drought event measures. This differs from most studies, which typically only estimate the impact of rainfall variability in different periods or years of childhood (Rocha and Soares 2015; Omiat and Shively 2020). Cumulative drought measures allow us to examine distinct natural experiments, potentially identifying different impacts of early life shocks in different regions and years. The approach helps mitigate concerns about confounding shocks that may influence the relationship between child health and drought (Dinkelman 2017; Dimitrova 2021). Third, the chapter extends the literature that examines the long-term and intergenerational effects of early life adversities by investigating how climate variability affects SES in adulthood and spill over into the next generation (Hyland and Russ 2019). Finally, this study contributes to the literature by examining the mechanisms of intergenerational health transmission. We explore SES as a potential pathway that links drought to child health, alongside the biological and environmental pathways.

Our analysis yields insightful findings that aid in gaining a deeper understanding of the relationship between drought, health and socioeconomic outcomes. Our results show that cumulative drought exposure during a women's childhood is negatively associated with wealth index, years of formal school and weight. These results are expected, and in agreement with Maccini and Yang (2009), Hyland and Russ (2019) and Weldesenbet (2022) who

document the long term impacts of weather shocks in Indonesia, in 19 African countries and in Tanzania respectively. Moreover, we find that mothers who experienced drought decades earlier have an increased likelihood of giving birth to more girls and to low birthweight sons and their children are more likely to be underweight. These results are in line with Dimitrova (2021), Dasgupta and Robinson (2023), Abiona (2024) amongst others, who found that drought adversely impacts child health in Ethiopia, Burkina Faso and Sierra Leone, respectively. Additionally, our findings suggest that boys are affected by rainfall deficit *in utero* and they have an increased likelihood of being underweight whereas the effects of drought on girls appear to be more mixed. Moreover, we find that the indirect effects of wealth and education mediates the effects of drought on child health in rural Kenya, particularly during severe drought. The results are in line with the literature that shows that parental socioeconomic status can shape a child's health trajectory and contribution to socioeconomic inequalities in adulthood (Aizer 2019; Houweling and Grünberger 2024).

1.3 Can Rainfall Serve as a Remedial Investment for Low Birth Weight Children?

The critical importance of the first 1000 days of life, *in utero* period included, and how adverse conditions experienced during this period can negatively affect life outcomes, including educational attainment, adult employment, and earnings is established, as is the need for catch-up growth (Alderman, Hoddinott, and Kinsey 2006; Deschênes, Greenstone, and Guryan 2009; Almquist 2016; Rosales-Rueda 2018; Thiede and Strube 2020). Research suggests possible remediation of adverse health in early childhood (Heckman 2011; Aizer 2019), but, while the importance of child growth is well established, it is equally important to determine the interventions and factors that contribute to catch-up growth.

Around the world, low birth weight (LBW) is a major public health problem, with subsequent short and long-term impacts. LBW represents about 15.5 percent of all live births,

with more than 90 percent occurring in developing countries (United Nations Children's Fund (UNICEF) 2019). The literature reports a strong relationship between LBW and adverse health conditions, such as: infant mortality, cerebral palsy, blindness, hypertension, and coronary diseases later in life. LBW has also been related to adverse socio-economic outcomes, such as poor cognitive skills, reduced employment and earnings (Almond, Chay, and Lee 2005; Camacho 2008; Cutland et al. 2017; Soliman et al. 2021; Bougma et al. 2022).

Remediation is therefore important for LBW children, if there is hope for them to thrive; the literature, thus, often considers catch-up growth to be important for LBW children to reach their full potential in life. Catch-up growth refers to improved anthropometric outcomes, namely weight and height, from an initial disadvantage (Anand et al. 2018). However, estimates of catch-up growth differ, depending on the definitions and metrics used. The various definitions are summarised as absolute (raw) and relative catch-up growth (Desmond and Casale 2017). Absolute catch-up growth occurs if the absolute weight deficit in kilograms decreases over time, i.e., if the weight-for-age difference (WAD) declines (Leroy et al. 2015). Relative definitions refer to catch-up growth as an improvement in weight-for-age (WAZ), they are more commonly used in the literature (Victora et al. 2010; Outes and Porter 2013; Desmond and Casale 2017; Anand et al. 2018; Casale, Desmond, and Richter 2020).

While the importance of child growth is indisputable, it is equally important to examine interventions and factors that potentially contribute to catch-up. In doing so, we investigate if positive rainfall shocks, which are beneficial events in an agrarian arid and semi-arid setting, are capable of supporting catch-up. For the analysis, we leverage the exogeneity of rainfall. One concern in an analysis of this sort is that any intervention related to child health could be related to unobserved parental investments and/or genetic potential, such that the treatment effect could be biased and inconsistent (Outes and Porter 2013; Adhvaryu et al. 2023). Rainfall, on the other hand, is unlikely to be correlated with genetic potential.

However, it might complement or substitute for other parental investments. In such an instance, which is the one we examine here, unobserved parental investments would be a mediator between rainfall and child health, such that the rainfall intervention estimate would be the non-mediated effect of rainfall. Moreover, we contribute to the understanding of the other factors associated with the incidence of catch-up growth, such as maternal height, education, and economic status.

Closely linked to remediation is the notion of critical periods. There is a debate in the literature concerning the period during childhood that is more sensitive to (or supportive of) catch-up growth and yields increased returns. Some researchers argue that investing in children at a very young age provides the highest returns to investment (Cunha, Heckman, and Schennach 2010; Heckman, Pinto, and Savelyev 2013) and that catch-up from nutritional deficiencies is reduced after the child's second birthday (Victora et al. 2010). However, recent work suggests the possibility of catch-up on both physical and cognitive dimensions after age two (Hirvonen 2014; Lundeen et al. 2014; Adhvaryu et al. 2023). We further this discussion by comparing catch-up growth at ages two and four years to determine if catch-up continues after the first two years of life.

Hence, we contribute to the literature in three ways. First, we extend the catch-up growth measurement discussion, as we analyse whether catch-up growth occurs at ages two and four years. We use both the absolute and relative definitions of catch-up growth in weight. Second, we contribute to the debate concerning the period during childhood that is more sensitive to catch-up growth by comparing catch-up growth at ages two and four years to determine if catch-up continues after the first two years of life. Third, although we are not able to directly address the issue of endogeneity associated with factors that influence catch-up growth, via, for example, instrumental variables, we do address it indirectly. Endogeneity may arise, because catch-up growth estimates are based on data from two different time periods, and the relationship between the two periods may be affected by unobserved confounders. In particular, the outcomes and investments are influenced by the preferences

of parents and the resources available to families (Adhvaryu et al. 2023), as well as the child's genetic potential (Outes and Porter 2013). We exploit the quasi-random nature of rainfall exposure to uncover estimates of catch-up growth for LBW children. Such rainfall is expected to be correlated with family resources and will likely affect resource-based decisions; however, our focus on exogenous rainfall impacts allows us to interpret the results as causal, even though we do not explore the pathways through which the affect operates. For the analysis, our specific focus is on whether positive rainfall helps generate catch-up growth in weight in LBW children in developing countries (Kenya), where interventions to remediate adverse early life conditions are scarce. We leverage the fact that positive rainfall is a beneficial event in ASALs. Also, in an agrarian setting with rainfed agriculture, such as Kenya, weather plays a crucial role in determining household income and nutrient intake, which has implications for child health.

The results indicate that there is catch-up growth in weight from one to four years. This suggests that LBW children can achieve nutritional catch-up after their second birthday (Outes and Porter 2013; Casale, Desmond, and Richter 2020). This catch-up growth is observed in both absolute (WAD) and relative (WAZ) dimensions. These results are in line with other studies on the role of health interventions in lessening the adverse impact of disadvantage in early childhood (Heckman 2011; Heckman, Pinto, and Savelyev 2013; Bharadwaj, Løken, and Neilson 2013; Campbell et al. 2014; Conti, Heckman, and Pinto 2016; Lynch and Gibbs 2017; Aizer 2019; J. L. García et al. 2020).

1.4 Impact of Environmental and Socioeconomic Factors on COVID-19 Transmission in Cape Town

The Coronavirus Disease 2019 (COVID-19) pandemic led to increased need for medical services in health systems that were not prepared to cope (Adabavazeh, Nikbakht, and Tirkolaei 2023; Paschoalotto et al. 2023; Ardakani et al. 2023). Poor health, strained health

care systems, and government regulations, further dampened economic activity around the world (Nicola et al. 2020; Ardakani et al. 2023) with developing countries amongst the most affected (Nicola et al. 2020; Ozili 2021; Naseer et al. 2023; Angelov and Waldenström 2023). South Africa was one of the most affected countries on the continent. As of May 2023, South Africa accounted for more than 40 percent of the total confirmed COVID-19 cases in Africa.¹ To curb the spread of the virus and prepare the health systems for the influx of patients, the government in South Africa implemented a strict lockdown for five weeks from March 26, 2020. Most economic activities across the country were restricted, apart from essential services, which included healthcare, security, agriculture, and the transport of selected goods (Asmal and Rooney 2021). Subsequently, the restrictions were gradually eased through five levels, with the strongest lockdown period classified as level 5. However, South Africa's efforts to control the COVID-19 pandemic significantly impacted the country and its population. According to Statistics South Africa (Stats-SA),² GDP shrank by 7.0 percent in 2020, compared to 2019, marking the largest decline in economic activity since 1946. The labor market was also heavily affected, with approximately 2.2 million people losing their jobs in the second quarter of 2020 (Köhler et al. 2021). Women's employment fell by 22.5% between February and April 2020, due to the stringent lockdown, while men's employment declined by 9.8% (Casale and Shepherd 2022).

There is evidence that human viral outbreaks follow seasonal cycles. Influenza and Human Coronavirus (HCov) display seasonal trends in temperate regions and are characterised by high transmission during winter months. These viruses mainly spread through airborne transmission via expelled droplets suspended in the air as aerosols for long periods of time (Shaman and Kohn 2009; Tamerius et al. 2013). Such cycles are associated with meteorological factors, human activity patterns, immunity and human-to-human contact, amongst others.

¹<https://who.maps.arcgis.com/apps/dashboards/0c9b3a8b68d0437a8cf28581e9c063a9>. Accessed on June 20, 2024

²<https://www.statssa.gov.za/?p=14074>

The literature, including recent reviews (Mecenas et al. 2020; Mcclymont and Hu 2021; Dong et al. 2021; Weaver et al. 2022) and global studies (S. Yuan, Jiang, and Li 2020; J. Yuan et al. 2021b; Liu et al. 2022; Nottmeyer et al. 2023) have investigated the relationship between temperature and relative humidity, as the most influential meteorological factors for Covid-19 incidence and mortality. However, these studies are inconclusive with some finding positive and others finding negative associations. The variation in the results are plausibly explained by differences in measurement of events, differing statistical methods with varying degrees of sophistication, differences in spatial scaling of the analysis and relatively short time series, any of which may induce significant biases. Moreover, the research on the relationship between COVID-19 and weather patterns has focused on the Northern Hemisphere, with few studies in developing Southern countries (Wang et al. 2023).

Therefore, it is important to attempt to disentangle the complex interaction of variables affecting the transmission of COVID-19. Understanding the transmission dynamics can enhance preparedness for future pandemics, ensuring that countries, particularly developing countries, are better prepared to prevent and respond to infectious disease threats. It can also uncover disparities in health outcomes and access to care, potentially leading to policy action that might address various social determinants of health, such as crowded living conditions or limited access to healthcare (Kissler et al. 2020; Leach et al. 2022).

Thus, we complement the existing literature on the role of meteorological factors and COVID-19 transmission in four significant ways. We use an extended study period from March 15, 2020, to January 24, 2021. The period covers approximately ten months, including the winter and summer seasons, in order to capture the seasonal effects of meteorological factors. Short study periods have been identified in the literature as a potential source of bias for the initial studies on the climate variables on COVID-19 transmission relationship (Dong et al. 2021; J. Yuan et al. 2021a). Second, the association between temperature, relative humidity, and the transmission of COVID-19 has generally been investigated with generalised linear models, wherein a quasi-Poisson distribution

was specified. In this analysis, we examine both nonlinearity and dynamic lags, which are an important extension. Thus, temperature and relative humidity components were underscored through a distributed-lag nonlinear model (DLNM). The model offers a framework to describe the additional time (lag) dimension of the exposure-response association to capture both nonlinear exposure-responses and delayed effects. This model specification also allows for the inclusion of confounders, such as the day of the week and month of the year to control for trends, as well as various levels of government lockdown, ranging from 5 to 1, to account for non-pharmaceutical interventions (NPI).

Third, since meteorological factors are closely linked to socioeconomic factors, we investigate whether the underlying relationships are different in low and middle/high socioeconomic status sub-districts. Thus, cold and heat effects of daily ambient temperature, as well as dry and humid effects of daily ambient relative humidity, on the daily COVID-19 incidence were investigated, while distinguishing between low and middle/high socioeconomic status sub-districts. In addition, we investigate the relationship between lockdown measures and Covid-19 transmission in the different settings. Fourth, studies on the links between meteorological factors and COVID-19 transmission in developing countries are scarce (Wang et al. 2023). Thus, we contribute to this literature by investigating this relationship in the Western Cape Province of South Africa. Moreover, studies that have used robust models, such as the DLNM, to analyse the relationship between climate variables and COVID-19 transmission are global or country-level studies (J. Yuan et al. 2021a). The literature suggests possible discrepancies between global and city-level studies (Dong et al. 2021). The latter are thought to provide more accurate estimates, due to lower measurement error in the outcomes and exposures (Nottmeyer et al. 2023). Therefore, focusing on a specific city as the unit of study, like Cape Town, rather than the country, can yield insights (not previously available) into the association between meteorological factors and the transmission of COVID-19.

The results uncover a complex association between COVID-19 incidence, temperature, rel-

ative humidity, and socioeconomic status. Cold temperatures increased the risk of COVID-19 incidence in Cape Town during the study period. Those living in the middle/high socioeconomic status areas were estimated to be more vulnerable to cold, than those from low socio-economic status areas. Heat significantly lowered the risk of COVID-19 incidence in the low socio-economic status areas. In contrast, heat increased the risk in middle/high socio-economic status areas. Low relative humidity significantly decreased the risk of COVID-19 incidence, and the risk of humid conditions, in general, increased, with longer lags in all areas, and was statistically significant in the middle/high socioeconomic status areas.

2 CHAPTER 2 Water Scarcity and Intergenerational Transmission of Health Inequality

2.1 Introduction

Approximately four billion people live in conditions of severe water scarcity for at least one month of the year, and about half a billion experience severe water scarcity all year round globally (Mekonnen and Hoekstra 2016; Stringer et al. 2021). Climate change is predicted to further intensify water scarcity through declines in precipitation and increases in evapotranspiration rates. Hydrological cycles are expected to undergo extensive changes, trigger global shifts in precipitation patterns, and augment the severity and the frequency of extreme events (Distefano and Kelly 2017). According to the United Nations, by 2050, the number of people living in areas with severely stressed water will increase to 3.2 billion (World Meteorological Organization 2020). Water scarcity has several short-term and long-term welfare consequences. Precipitation deficits impact food systems and reduce agricultural production and nutrient intake, thus impacting health outcomes (Carpena 2019; Amondo, Nshakira-Rukundo, and Mirzabaev 2023). Moreover, it can affect the prevalence of vector-borne, waterborne and water-washed diseases such as diarrhoea, malaria, dengue fever affecting particularly young children's health through undernutrition. Bhutta, Aimone, and Akhtar (2019) estimate that children bear more than half of the disease burden from climate change and variability.

Children are more susceptible to suffering or dying from undernutrition due the intense nutrient requirements to satisfy their physiological development (Black, Trude, and Lutter 2020; Sudiyah and Rosida 2021). Undernutrition can cause structural damage to the brain, impair motor cognitive development of a child; it can increase the risk of developing chronic health conditions such as cardiovascular issues, diabetes, mental health problems, and respiratory diseases later in life (Black, Trude, and Lutter 2020). The impact of environ-

mental conditions on early childhood undernutrition have been found to progress through adulthood, influencing educational attainment, employment prospects, and overall well-being in the long run (Almond, Chay, and Lee 2005; Almond and Currie 2011; Currie and Vogl 2013; Cutland et al. 2017; Bougma et al. 2022; Weldesenbet 2022). Moreover, the socioeconomic disparities associated with environmental conditions early in life can be carried over to the next generation, perpetuating cycles of poverty and poor health outcomes (Aizer 2017; Hyland and Russ 2019; Straight et al. 2022).

In the last decade there has been an increase in the number of studies on the impact of weather conditions on child health at birth (Grace et al. 2021; Abiona and Ajefu 2023), in the short run (Rabassa, Skoufias, and Jacoby 2014; Rocha and Soares 2015; Thiede and Strube 2020), in the long run (Maccini and Yang 2009; Yamashita and Trinh 2022; Weldesenbet 2022). However, this literature has mainly focused on the first generation impacts with less analysis of whether these effects are transmissible across subsequent generations (Tan, Zhang, and Zhang 2025). This chapter fill in the gap by studying the intergenerational transmission effects of drought exposure of mothers in early life on wasting and underweight of their offspring.

To examine aggregate rainfall effects on parents and investigate the potential transmission to next generation, we draw upon data from the Demographic and Health Surveys, accessed through Integrated Public Use Microdata Series database - IPUMS-DHS (Boyle, King, and Sobek 2024), and climate data from the renowned Climate Research Unit's Time-Series (Harris et al. 2014, 2020). We compute the Standardised Precipitation Index (SPI) for each District per year using the monthly precipitation series from 1950-2014, following McKee, Doesken, and Kleist (1993). This approach allows us to construct a cumulative measure of drought exposure in a child's earliest life, aligning with the approaches of Dinkelman (2017) and Hyland and Russ (2019). Subsequently, the linked dataset is then used to investigate the impacts of rainfall fluctuations on the parents (first generation) and then their offspring (second generation) in Kenya, a country with more than 70 percent of its land characterised

as Arid and Semi-Arid with recurrent water scarcity.

We first ask how cumulative droughts experienced during early life, including the *in utero* period affect the socioeconomic outcomes (wealth and education) and health (weight and BMI) of mothers. Cumulative drought measures allow us to consider distinct natural experiments, possibly identifying different impacts of early life shocks in different regions and years. This approach helps mitigate concerns about confounding shocks that may influence our findings on the correlation between child health and a single weather event. Using this strategy provides a robust framework for analysing the adverse effects of droughts on long term outcomes that is both comprehensive and reliable (Dinkelman 2017). Since drought events are quasi-random within and across districts on a year-to-year basis, we can compare the health of mothers born in districts affected by drought with those born in non-affected districts across different birth years (Maccini and Yang 2009; Rocha and Soares 2015). A number of studies have documented the role of climate variability in childhood in shaping later life outcomes such as wealth, educational attainment and welfare (Abiona 2017; Hyland and Russ 2019; Yamashita and Trinh 2022; Chang, Favara, and Novella 2022)

We then test whether there is an intergenerational impact of early-life drought. We focus on a wide range of outcomes including the likelihood of being underweight, wasted instead of focusing only on the birth weight of the respondents' children as in Hyland and Russ (2019). We define dummy variables that are equal to one if a respondent's child is either underweight, wasted or has a low birthweight. We further analyse these effects by gender to explore whether drought effects are gender specific.

Furthermore, the intergenerational transmission of health involves complex biological, epigenetic, environmental, socioeconomic and behavioural mechanisms that influence health outcomes across generations as highlighted in recent studies (Galler and Rabinowitz 2014; Moog et al. 2022; Racine et al. 2023). Hence, we ask whether socioeconomic status (SES) is a mechanism through which drought's effects are transmitted to the next generation. We

capture SES through the wealth index and the total years of education. We use mediation analysis to explore whether SES mediates the relationship between drought and child health in rural Kenya. SES as a mediator between parents' exposure to drought and their children's health has not been explicitly studied in the weather shocks literature. Thus, we use a mediation analysis to test that relationship.

Our results show that early life exposure to drought adversely affects long run outcomes of mothers with subsequent impacts felt by the next generation. We find that a one-unit increase in cumulative drought (when drought is defined as SPI values below -1.5) results in a reduction of 1.49 in the wealth index and 2.5 in years of schooling. Similar impacts are found for exposure to moderate drought during early life. Second, we find that experiencing drought in childhood for a mother increases the likelihood of having children who are either underweight or wasted. Moreover, the intergenerational effects of drought appear to be felt more by girls, indicating potential discrimination in resource allocation upon child birth. Additionally, we find that wealth and years of schooling seem to mediate the effect between drought and child health in the second generation.

This paper follows the empirical approach of Hyland and Russ (2019), who examine the long-term effects of childhood drought exposure on women in Sub-Saharan Africa and its potential transmission to the next generation. While their analysis focuses on educational, wealth, height and low birthweight outcomes, we extend their work by investigating more adulthood outcomes including weight and BMI and we specifically investigate how maternal drought exposure affects child health outcomes such as wasting, underweight and sex ratio. Additionally, we test the mechanisms of intergenerational transmission of long-term drought impact by analysing whether socioeconomic status mediates these effects. In doing so, this study provides new evidence on the persistence of climate shocks across generations.

Thus this chapter makes four significant contributions to existing literature. Firstly, it adds

to the growing body of research linking extreme weather events and various outcomes, including studies by Maccini and Yang (2009), Hyland and Russ (2019), Randell, Gray, and Grace (2020), Thiede and Strube (2020) and Dasgupta and Robinson (2023). Our specific focus on both adult and child outcomes allows us to expand upon previous research and shed light on how drought exposure during mothers early years impacts their socioeconomic status and health as adult. Secondly, we examine a range of weather shock periods and durations. We examine the effects of rainfall deficits during early life up to 4 years old, as well as the *in utero* period, focusing on cumulative drought event measures. This differs from most studies, which typically estimate the impact of rainfall variability in different periods or years of childhood (Rocha and Soares 2015; Omiat and Shively 2020). Cumulative drought measures allow us to examine distinct natural experiments, potentially identifying different impacts of early life shocks in different regions and years. The approach helps mitigate concerns about confounding shocks that may influence the relationship between child health and drought (Dinkelman 2017; Dimitrova 2021). Third, the chapter extends the literature that examines the long term effects of early life adversities by investigating how climate variability affects SES in adulthood and spill over into the next generation (Hyland and Russ 2019). Finally, this study contributes to the literature by examining the mechanisms of intergenerational health transmission. We explore SES as a potential pathway that links drought to child health, alongside the biological and environmental pathways.

Our study focuses on Kenya, a developing country where more than 80 percent of the land surface comprises Arid and semi-arid lands (ASALs), and drought events and water scarcity are recurrent. For instance, in the last 100 years, Kenya has experienced over twenty-five droughts (Bank 2021) and the frequency and severity of droughts over the past decade is increasing. Most recently, the drought that struck the Horn of Africa in 2020-2022 was classified as the worst in four decades, surpassing previous droughts in terms of duration and severity. As of October 2022, 4.2 million people in Kenya were already affected (UNFPA 2022; ACF & IFPRI 2023).

The remainder of the chapter is organised as follows: Section 2 and 3 provide a brief literature review and background, respectively. Section 4 discusses the data, while Section 5 covers the empirical strategy. Section 6 presents the results of the main empirical analysis, while Section 7 examines the mechanisms linking rainfall deficits and health outcomes in the second generation. Section 8 discusses the results and Section 9 concludes.

2.2 Literature review

The impact of climate variability on short and long-term outcomes is a global concern that is increasingly being recognized. Previous research on the effects of early life shocks has been skewed towards developed countries, mainly due to data limitations in developing countries. However, with the emergence of new data sources, researchers are now able to bridge this gap and explore the link between weather-related shocks and health outcomes (Currie and Vogl 2013). This is particularly significant as changes in weather patterns have a significant impact in developing countries where the population's livelihood is profoundly tied to rainfall (R. Hanna and Oliva 2016).

The literature has established that children are particularly vulnerable to climate shocks, especially when exposed to extreme weather during the first 1000 days of life, including the *in utero* period. For instance, Rocha and Soares (2015), Davenport, Dorélien, and Grace (2020) and Abiona and Ajefu (2023) find that rainfall deficits experienced during the *in utero* period decrease the gestational period, augment the likelihood of preterm birth and low birthweight in Brazil, 13 African countries and Sierra Leone, respectively. Researchers also investigate how exposure to climate variability beyond the prenatal period impact child anthropometrics (Abiona 2017; Davenport et al. 2017; Thiede and Strube 2020; Randell, Gray, and Grace 2020; Omiat and Shively 2020; Ngwira 2020; McMahon and Gray 2021; Dimitrova 2021; Weldesenbet 2022; Van der Merwe, Clance, and Yitbarek 2022; Yeboah et al. 2022; Njatang, Djourdebbé, and Wadou 2023).

Nonetheless, the focus of the previous research on the impact of weather-related effects has been on the first generation without much investigation of the potential spillover effect on the next generations. There are only a few studies that examine the effects of climate variability experienced by parents in their early life and the subsequent impact on their offspring (Mussa 2017; Hanjahanja-Phiri 2018; Hyland and Russ 2019; Clance, Getachew, and Yitbarek 2024). Hyland and Russ (2019) analyse the long-term impacts of drought exposure on women in 19 countries in Africa and find that women who experienced drought during childhood were less wealthy as adults and attained fewer years of education. Moreover, these effects were transmitted to the next generation as maternal drought exposure increased the likelihood of low birthweight among their children. A study in Malawi by Hanjahanja-Phiri (2018) analyses the intergenerational effects of Maternal exposure to drought in utero on newborn size. The study finds no effect of maternal drought exposure on offspring birthweight but uncovers a negative impact when drought occurred in the second to third semester of gestation, specifically reducing children's Length-for-Age z scores. Mussa (2017) and Clance, Getachew, and Yitbarek (2024) investigate the relationship between climate shocks and intergenerational education mobility in Malawi and Ethiopia respectively. The findings show that in Malawi, birth-year rainfall shocks reinforce intergenerational educational mobility between mothers and their daughters only. In contrast, in Ethiopia experiencing climate shocks as parents during childhood reinforce the persistence of intergenerational education with their sons. This points to a potential limiting effect of early-life rainfall-related income shocks on equality of opportunity. We contribute to the literature by analysing the long-run effects of maternal exposure to drought during childhood in Kenya and extend it by investigating spillover effects of early drought exposure on multiple outcomes in the next generation.

Another strand of the literature examines the intergenerational effects of early life adversity. For instance, several studies have examined the long-term and intergenerational impacts of the Great Chinese Famine (1959-1961): Tan, Tan, and Zhang (2023) finds that children

whose fathers were born in rural areas during the famine years had impaired cognitive abilities, with a more pronounced effect on daughters, indicating the role of son preference in resource allocation within families. And in a recent study, Tan, Zhang, and Zhang (2025) investigate the mental health outcomes of famine survivors and their offspring, finding that early exposure to famine increased the risk of mental illness in women but not men. Furthermore, the second-generation effects were observed among the sons of male famine survivors, suggesting a potential cultural mechanism related to son preference. Childhood maltreatment and its impact on future generations has also drawn a lot of attention in the literature. A systematic review and meta-analysis by L. Zhang et al. (2023) and Sakti et al. (2023) find that parents who experienced adverse childhood events (ACEs) were more likely to have children with mental health problems, including increased risks of internalising and externalising disorders. However, the review also noted that parental ACEs were not significantly associated with offspring's cognitive or language development, suggesting that certain domains of child development may be more resilient to intergenerational transmission. Beyond psychological and cognitive outcomes, research also highlights the intergenerational transmission of health behaviors such as smoking and alcohol consumption with parental habits playing a significant role in shaping children's behaviors (Kalmijn 2022).

Finally, the literature identifies various mechanisms through which intergenerational health is transmitted including biologic and epigenetic modifications, parental health behaviors, and socioeconomic conditions, all of which contribute to shaping the health trajectories of future generations. For instance, Giuntella, La Mattina, and Quintana-Domeque (2023) find that both maternal and paternal birth weights are significant predictors of a child's birth weight, suggesting a genetic and environmental basis for health at birth. Epigenetic research also provides deeper insights into how early-life experiences shape future generations. Studies indicate that maternal stress, malnutrition, and adverse childhood experiences (ACEs) alter gene expression through DNA methylation, which can influence off-

spring health even before birth. Moreover, Socioeconomic status (SES) has been found to play a role in determining health outcomes across generations (Aizer 2017; Houweling and Grünberger 2024). These pathways are interconnected and may work together.

However, in the weather shock literature, the mechanisms of intergenerational transmission of rainfall shocks remain largely unexplored. Hyland and Russ (2019), highlight that early-life rainfall shocks affect women's empowerment later in life, potentially contributing to the intergenerational transmission of environmental shocks. Straight et al. (2022) find that maternal exposure to drought the year before child birth led to epigenetic changes in offspring, affecting immune function and metabolic health. We contribute to the literature on the mechanisms of intergenerational transmission of health by analysing the mediating effect of SES between drought and child health.

Given the depth and number of occurrences of droughts, Kenya is often considered in the literature. However, we extend this literature, as well. Grace et al. (2012) used the DHS survey data to investigate the relationship between climate variables and child stunting, a measure of malnutrition. They find that warming and drying increases child malnutrition. However, the study does not include a direct measure of drought. Bauer and Mburu (2017) used a small household panel to analyse the impact of drought on child health in the Marsabit district of Kenya. Using mid-upper arm circumference (MUAC) as the health measure and normalized difference in the vegetation index (NDVI) as the drought measure, they show that an increase in NDVI z score reduces the likelihood of child undernutrition. Ongudi and Thiam (2020) investigated the effects of drought on child nutrition and the potential for cash transfers to mitigate the effects of weather shocks in childhood in four districts of Northern Kenya. Their research focused on the Hunger Safety Net Programme (HSNP), which may not be as representative as the DHS. They constructed drought measures using the Standardized Precipitation Evapotranspiration Index (SPEI) and observe that drought reduced the HAZ and wlt scores in children. Thiede and Strube (2020) analysed the impact of climate variability on child edc in 18 countries, including Kenya. They find that above-

average temperatures and below-average precipitation reduces edc. However, they used temperature and precipitation anomalies to measure climate variability, while we use SPI which is a more general indicator that allows for comparison across regions with markedly different climates, since it can be used for both dry and rainy seasons. Njatang, Djourdebbé, and Wadou (2023) examined the impact of climate and armed conflict on the prevalence of underweight in some districts of Kenya. Like Bauer and Mburu (2017), they used the normalised difference in vegetation index (NDVI) to measure drought. They find that higher than average precipitation reduces the prevalence of moderate underweight. However, they were not able to consider both the timing and period of exposure to drought. A study by Straight et al. (2022) find that exposure to drought while *in utero* led to epigenetic changes in offspring, affecting immune function and metabolic health. The above studies identified the effects of *in utero* or early life drought exposure on the first generation only. Hence, we complement this literature on Kenya by examining the impact of maternal drought exposure on the next generation and investigating the socioeconomic status (SES) of exposed mothers as another mechanism through which drought is transmitted across generations.

2.3 Background

This paper focuses on Kenya, a country located in east Africa. Over 80% of the country's land is classified as Arid and Semi-Arid Lands (ASALs)³, and is home to about one-third of the total population (The World Bank 2018). Drought is the most common natural hazard in Kenya and the risks from persistent droughts have increased with Northern Kenya alone experiencing 28 major droughts over the past 100 years at increasingly frequent intervals (Ndegwa and Kinyua 2018). Droughts are estimated to affect more people and have a greater economic impact on the country (Bank 2021); the severity and frequency of droughts in the country appear to be increasing over time. For example, the 2011 drought was considered a major event, with 3.75 million people affected, nearly annual droughts

³Map of Kenya included in Appendix, Figure J.1, source:Chaudhury, Summerlin, and Ginoya (2020)

were recorded in Kenya in 2012 and 2016 (Haile et al. 2020; Ondiko and Karanja 2021), while the 2016/2017 drought was officially declared a national disaster (Uhe et al. 2017; Ondiko and Karanja 2021). Most recently, the drought that struck the Horn of Africa in 2020-2022 was the worst in four decades in terms of duration and severity and as of October 2022, 4.2 million people were already affected in Kenya (UNFPA 2022; ACF & IFPRI 2023). This trend is likely to continue or worsen, due to expected changing global climate (Distefano and Kelly 2017; IPCC 2023).

2.3.1 Water scarcity in Kenya

According to Falkenmark Indicator⁴, a country is designated as “water stressed” if water availability per capita is below 1700 m^3 per year. Kenya is below even this level; its annual water availability is 1000 m^3 per capita (Mulwa, Li, and Fangninou 2021). In 2014, according to the Demographic and Health Survey (DHS), of the estimated 43 million Kenya’s population, 31.6% were using unimproved drinking water sources – 13.2% use unprotected dug wells and springs, tanker trucks or carts with drums while 18.4% use surface water. The urban population had the highest percentage of pipe water at 85.7%, while nearly half of the rural population rely on unimproved sources (DHS 2014; Yu et al. 2019). One of the issues affecting access include water management. For example, the ASALs are situated downstream of the major catchment areas of Kenya, which are classified as “low potential” areas for agriculture thus receiving only a small portion of allocated water extraction rights which increase their reliance on rainfall. Water scarcity is further worsened by droughts, which affect both surface and groundwater resources, reduce water supply, deteriorate water quality and lead to crop failure (Omondi 2014; Yu et al. 2019; Mulwa, Li, and Fangninou 2021).

⁴The Falkenmark Indicator, is a ratio of a country’s water footprint to its total renewable water resources, which include ground and surface water (blue water) and moisture stored in soil strata (green water). The higher the index, the more pressure a country faces on its water resources (Ding and Ghosh 2017)

2.4 Data and key variables measurement

2.4.1 Data sources

We use data from two main sources in this study. The first is the Kenyan 2014 Demographic and Health Survey (DHS) which we extract from the Integrated Public Use Microdata Series database, IPUMS-DHS. Observations are organised by district. The second dataset is the gridded weather data from the University of East Anglia Climate Research Unit Time Series (CRUTS) where we extract the rainfall data used to construct the Standard Precipitation Index (SPI) by district by year. We then merge DHS and the weather data (SPI) by district by year.⁵ The subsequent sections present a comprehensive description of the data used in this study.

Demographic Health Survey (DHS)

Anthropometric and socioeconomic data used in this analysis is extracted from the 2014 Kenya Demographic and Health Survey (DHS) (DHS 2014). The 2014 Kenya Demographic and Health Survey (2014 KDHS) was implemented by the Kenya National Bureau of Statistics from May 2014 to October 2014 in partnership with the Ministry of Health, the National AIDS Control Council (NACC), the National Council for Population and Development (NCPD), and the Kenya Medical Research Institute (KEMRI). We access DHS data through the Integrated Public Use Microdata Series database, IPUMS-DHS (Boyle, King, and Sobek 2024). The IPUMS-DHS design improves the ease of use and facilitates the analysis of DHS data across time and countries. For instance, IPUMS-DHS provides researchers with merged DHS files related to a single survey, removing one of the

⁵Data cleaning and preparation is done with Stata version 15.1. For the analysis, we use R version 4.4.1 (R Core Team 2023) with the following packages: `haven` (Wickham 2023) to import foreign statistical formats (mainly Stata) into R; `tidyverse` (Wickham 2023) to import, clean, manipulation, transform and present the data; `stargazer` (Hlavac 2022) for results tables, `knitr` (Xie 2024) for dynamic report generation in R; `kableExtra` (Travison et al. 2024) to construct complex tables and customize them, as needed; `lmtest` (Hothorn and Zeileis. 2022) to test regression results; `ggdag` (Barrett 2024) to illustrate our mediation model, `mediation` (Tingley et al. 2014) for estimation of the direct indirect effects, and, particularly, confidence intervals around those effects. We further use `rmarkdown` (Allaire et al. 2024) to combine R codes, results from the data analysis and the text into one reproducible document.

biggest challenges for users of DHS data. The DHS surveys are nationally representative cross-sectional household surveys widely used in health research in the developing world, particularly in sub-Saharan Africa. These surveys administer a core questionnaire focused primarily on women aged 15 to 49 years and their children aged 0-59 months. The questionnaire includes information on maternal health, fertility and family planning, anthropometry, child mortality, and morbidity. Furthermore, socioeconomic information such as education levels and employment of women are also included.

The Kenya DHS (2014) draws from the National Population and Housing Census 2009. Kenya is divided into 47 counties (districts) spread over 8 provinces, which serve as administration units. Each of the 47 counties is stratified into urban and rural groups, resulting in 92 strata, since two counties are entirely urban. A total of 39,679 households were selected for the survey. The final sample comprised a total of 36,430 households that were interviewed, including 13,914 from urban areas and 22,516 rural areas. The household response rate was high at 99%. The survey used a household questionnaire and observational checklist for collecting the information.

The IPUMS-DHS offers three universes: Women, Children and Men. A universe is defined as the population responding to the question or, in the case of children or births, the population to whom the question applies. In this thesis, we use the children universe. Besides children anthropometrics, the DHS further provides information on the mother's socioeconomic characteristics such as age, the number of children ever born, educational attainment, and wealth asset index. It also includes household characteristics, such as source of drinking water, time spent fetching water, type of sanitation facility, and type of building, etc. Given the absence of data on maternal or child place of birth in the 2014 DHS, we adopted the simplifying assumption that the mother's current place of residence reflects the place of birth for herself and her child. While this may not capture all migration dynamics, it allowed us to align individuals with relevant district-level exposures. This assumption is based on data from the 2009 Kenya Population and Survey Implementation Housing Census, that show

around only 2.5 % of the sample reported changing residence to a different major administrative unit after 1 year suggesting minimal potential for bias due to migration. Also the literature shows that Kenya's internal migration is characterized largely by rural-to-urban whereas within-district moves are small (International Organization for Migration (IOM) 2015; Mueller et al. 2023). Since the exposure variable, SPI, is defined at the district level and our focus is on rural households, within-district migration does not alter an individual's exposure classification as it does not involve a change in administrative or environmental context. Therefore, we expect such movements to have minimal impact on our results.

The dataset contains 20,964 observations. For our analysis, we focus solely on rural households, where drought and water scarcity are expected to matter more, due to reliance on rainfall. After limiting to rural mothers who currently residing in the rural Kenya, we were left with 14,136 observations. We further remove observations containing missing values, after doing so, we are left with 10,492 observations for our analysis. In a subset analysis, focusing on the the impact of drought during the *in utero* period, we further limited the data to mothers born in January, such that their entire *in utero* period occurred during the year before birth. Doing so limits ambiguity with respect to the year in which the drought was recorded, and yielded only 1018 observations.

We acknowledge that other Kenya DHS surveys with cluster-level GPS data could have been used potentially offering an alternative to district-level identifiers. However, our decision to use the 2014 DHS was guided by several practical and methodological considerations (i) At the time we started this investigation, the 2014 DHS was the most recent Kenya DHS providing comprehensive coverage of child anthropometric indicators, maternal characteristics, and household-level variables necessary for our analysis; (ii) Our primary exposure measure, the Standardized Precipitation Index (SPI) is defined at the district level, making the use of district identifiers both appropriate and consistent with the spatial scale of environmental shocks. Using GPS coordinates would have required interpolating SPI data to the cluster level, which might require additional assumptions and potential spatial noise;

(iii) Districts (counties) replaced the former provinces as the main administrative divisions following the 2010 Constitution. Each county has its own government, with a governor and county assembly, responsible for local administration and service delivery. Thus, analyzing data at this level allows for clearer implications for planning and interventions; (iv) We extract DHS data through the IPUMS-DHS platform which facilitates easier harmonisation and aggregation of multiple DHS samples across time. However, the IPUMS-DHS version of the most recent Kenya DHS (2022) has not yet been released. Therefore, while GPS-based methods may offer finer spatial precision, our district-level approach remains methodologically sound and policy-relevant given the structure of our exposure data and the available IPUMS-DHS release formats. We also view this as an area for future research when updated IPUMS-DHS data becomes available.

Rainfall data

Monthly rainfall data were used to measure drought. In Kenya, when dealing with rainfall measurements, two types of rainfall data can be considered, synoptic data sourced from the Kenya Meteorological Department (KMD) and gridded rainfall data. In this study, we use gridded monthly rainfall data instead of station data, since spatial and temporal discontinuities exist over large sections of the observational East African rain-gauge data, especially from the post-independence era of the 1970s through to recent years. Such gaps likely reflect on the reliability of station data (Ayugi et al. 2019). The gridded data, available from the University of East Anglia Climate Research Unit's Time Series (CRUTS) (Goodman et al. 2018) fills these gaps by interpolating data from over 4000 weather stations. The data is available on a spatial resolution of 0.5 x 0.5-degree scale from 1901 to date. Detailed information on various versions of the data is provided by Harris et al. (2014) and Harris et al. (2020). We acknowledge that 0.5 x 0.5-degree spatial resolution is coarse when compared to finer-grained datasets like ERA5-Land. However, the continued use of such data in economic research is often a practical trade-off balancing between spatial granularity, computational feasibility and historical continuity. Many economic studies still rely on these

coarser datasets for various reasons including longer historical records extending back to the early 20th century and the ease of integration with health and economic outcomes which are often only available at the national or district level. Coarser weather data, which averages well over larger areas, aligns better with these economic aggregates. Also, several influential economic papers have built robust empirical strategies using coarse-resolution weather data (Dinkelman 2017; Thiede and Strube 2020).

Using the monthly precipitations series from 1950-2014, we compute the Standardised Precipitation Index (SPI) following (McKee, Doesken, and Kleist 1993) by district by year with values measured at 12 month intervals. SPI is a probability index that requires only monthly precipitation for its computation. The index allows for comparison across regions with markedly different climates, since it can be used for both dry and rainy seasons. It is also computed for different time scales to suit various meteorological, agricultural, and hydrological applications. The SPI is obtained by fitting a gamma or a Pearson Type III distribution to monthly precipitation values to transform the data, such that the annual averages are normalised. Thus, SPI is the number of standard deviations that the observed value would deviate from the long-term mean. In line with the climatology literature (McKee, Doesken, and Kleist 1993) and following (Dinkelman 2017; Hyland and Russ 2019), we define drought in a district and year to be 1 for values of the SPI less than -1.5 and 0 otherwise – we allow for other definitions based on different SPI thresholds as discussed in other parts of the chapter. The SPI is yearly because our analysis is mainly at the year level whereby cumulative drought measures are the fraction of years spent in drought (Dinkelman 2017) and also individual measures of drought include year before birth, after birth etc. Moreover, yearly measures provide a stable overview by smoothing out fluctuations for clearer trends across years and are easier to interpret for various stakeholders.

We use the Standardized Precipitation Index (SPI) as our preferred measure of climatic variability for the following reasons: SPI requires only precipitation data, which is more widely available and less prone to measurement error compared to the multiple variables needed

to compute potential evapotranspiration (PET) for SPEI (e.g., temperature, radiation, wind speed and humidity). This is particularly important in data-scarce settings like rural regions of developing countries. SPI is a simpler and more transparent metric than SPEI in which PET calculations are often estimated using empirical models such as Thornthwaite or Penman-Monteith, which might introduce assumptions and parameter uncertainty. Moreover, SPI is widely used in the economic, development, and climate-health literature, enabling easier comparison with prior studies (Dinkelman 2017; Hyland and Russ 2019; Cooper et al. 2019). We will consider using SPEI for our future research as it takes into account temperature and evapotranspiration. Figure 2.1 depicts the SPI from 1950-2014, highlighting rainfall variability over the period.

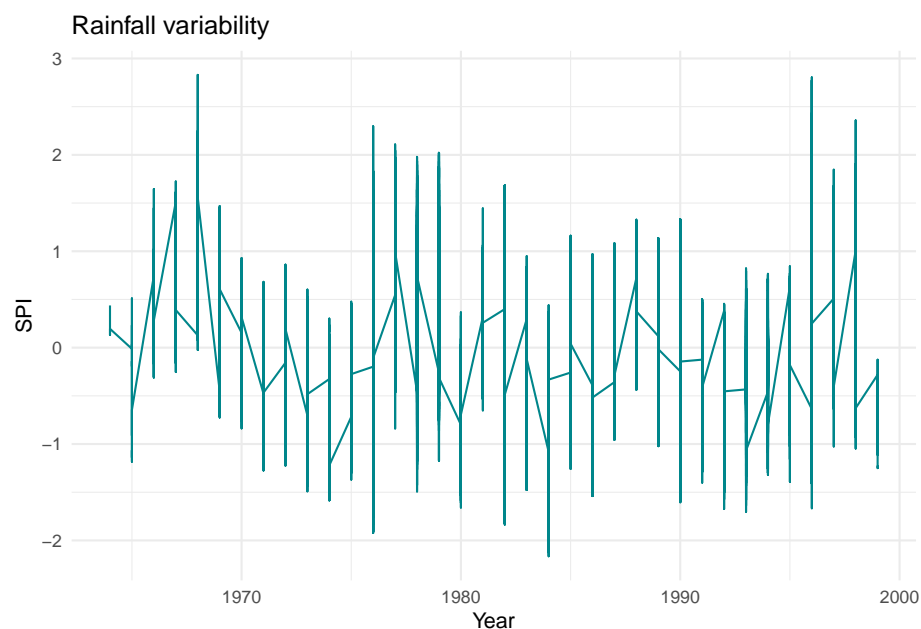


Figure 2.1: Rainfall variability (SPI)

2.4.2 Study variables

Drought measures

We define two major type of indicators to capture drought exposure. The first set includes cumulative measure of drought exposure in a mother’s earliest life, in line with Dinkelman

(2017) and Hyland and Russ (2019). It is the proportion of years from the calendar year before birth ($t-1$) to the fourth calendar year after birth ($t+4$), when SPI is less or equal to -1.5 in the district of residence. Measuring drought as a percentage of years spent in drought allows us to capture multiple drought events across many years, rather than relying on a single drought event. Studies that rely on a single event, such as drought (UmanaAponte 2011) or famine (Tan, Zhang, and Zhang 2025), face a number of empirical difficulties. For example, the duration of the event might be too brief to produce an impact. Furthermore, the event might impact a relatively small portion of the population, which might render it difficult to obtain reliable effect estimates that would normally benefit from large sample analysis (Shige Song 2014).

Our second set of indicators include single measures of drought namely drought *in utero*, in birth year and first year of life. Drought *in utero*, needs to be carefully defined, when using SPI to measure drought. In this study, SPI is calculated based on a calendar year. We define the *in utero* period as 12 months or a year before mother's birth. This definition brings in some measurement errors for mothers whose *in utero* period coincides with the year of birth. For instance, a born born in January 1990 has 1989 as its *in utero* period whilst for a mother born in December 1990, the *in utero* period is the same as the year of birth or 1990. To accurately capture the effects of drought during the *in utero* period, in this study, we consider only mothers born in January to capture their largest portion of their pre-natal period during the year before before birth ($t-1$).

Outcomes and potential confounders

For the first generation (mothers) analysis, we focus our attention on four long term outcomes: wealth, education, weight and body mass index (BMI). The wealth index provided in the DHS is a composite measure of the household's cumulative living standard. It is calculated based on households ownership of selected assets, such as televisions and bicycles, materials used for housing construction, and types of water access and sanitation

facilities. The education variable is a the total number of years of formal schooling. BMI is a health indicator derived from an individual weight and height which classifies individuals into different weight categories such as underweight, normal weight, overweight and obese. We also include few control variables in the analysis such as age, religion and ethnicity of mothers.

For the second generation analysis, five health outcomes are considered for the offspring: underweight or weight-for-age z scores (WAZ) < -2 ; wasting, weight-for-height z scores (WHZ) < -2 , stunting, height-for-age z scores (WAZ) < -2 ; sex ratio and Low birthweight (LBW). WAZ and WHZ are scoring systems that express anthropometric values as standard deviations relative to the mean or median of a reference population (Mei and Grummer-Strawn 2007). The literature captures the nutritional status and health of children between 0 and 59 months, through their weight and height. Wasting (Weight-for-Height < -2 SD) measures body mass in relation to height and describes current nutritional status. However, underweight, is a composite index of weight-for-age. It takes into account both acute malnutrition (wasting) and chronic malnutrition (stunting), but it does not distinguish between the two (Akombi et al. 2017).

2.5 Methods

2.5.1 Long-term impacts of drought exposure on women's socioeconomic and health outcomes

In order to identify the impact of early life drought exposure on wealth, education and health, we use the variation in drought events experienced in mothers' childhood as the exogenous experiment, where drought is assumed to be quasi-random within and across districts from year to year. In other words, we focus on local deviations in rainfall amounts from their long run local averages, where large deviations are unexpected and plausibly exogenous. Under that assumption, we can compare cohorts affected by drought and those not affected

by drought across birth years and districts (Maccini and Yang 2009; S. Kumar, Molitor, and Vollmer 2016; Dinkelman 2017). Therefore, birth information is merged with weather data by linking the year and district of birth with the district-specific rainfall measures. We then estimate the impact of early childhood exposure to drought using a standard specification.

$$Y_{ihd} = \beta_0 + \beta_1 Drought_{idt} + \beta_2 X_{ihd} + \mu_d + \omega_t + \epsilon_{ihd} \quad (1)$$

In the preceding, Y_{ihd} represents the outcomes of interest for respondent i from household h in location d . These outcomes are wealth, education, weight and BMI for the first generation analysis; underweight, wasting, stunting, sex ratio and low birthweight for the subsequent generation (offspring). $Drought_{idt}$ represents one of two drought measures defined previously: Cumulative Drought and Drought in-utero. β_1 is the coefficient of interest quantifying the effect of drought exposure. X represents other observable child and mother characteristics previously noted. Finally, we include province of birth fixed effects, μ_d , and birth year fixed effects, ω_t , such that ϵ_{ihd} is the idiosyncratic error term. We run one model for each child outcome using Ordinary Least Squares (OLS). The analysis is conducted at the district (county) level, involving 47 districts distributed across 8 provinces with standard errors clustered at the household level to account for intra-household correlation.

For robustness, we consider other drought indicators, such as exposure in the year of birth, as well as the year after birth, and a cumulative drought measure ranging from year of birth t to $t+2$. In addition, for the intergenerational analysis, we examine potential heterogeneity by separately exploring the impact of drought on male and female children, which might imply the presence of discriminatory resource allocation practices within familial contexts.

2.5.2 Channels of the impact of rainfall deficit on child health

In addition to examining the effect of drought, we attempt to shed light on the possibility that rainfall deficits impacts are mediated by the Socioeconomic status (SES) of the parents (mothers).

We use a simple mediation analysis to examine how drought (the independent variable) influences child health (dependent variable) through SES (mediator). A mediation analysis aims to identify and assess the mechanisms through which the independent variable (treatment) influences an outcome. This process allows us to break down the total effect into indirect and direct effects. The indirect effect occurs through an intermediary variable or mediator, while the direct effect encompasses all other possible reasons for why the treatment has an impact (Celli 2022). We do not intend to demonstrate causality, at this stage, although I will continue to explore that possibility in future work.

Consider Figure 2.2, a directed acyclic graph, which includes four nodes and six edges with directed arrows – arrows that point in one direction. Thus, the figure outlines our assumptions in the mediation analysis. As implied above, drought is assumed to be an (at least conditionally) exogenous treatment, which we denote by D_i . SES, $W_i(D)$ is our potential mediator of the effect of drought on child health Y_i , while potential confounders C_i are assumed to be correlated with D_i , W_i and Y_i . [Although drought is assumed to be exogenous, the preceding analysis included numerous additional controls, including location fixed effects that are likely correlated with drought and child health. Thus, our models were predicated on an assumption of conditional exogeneity. Following Robins and Greenland (1992), Imai, Keele, and Tingley (2010) and Tingley et al. (2014), amongst others, we estimate a mediator model $f(M|D, C)$ and an outcome model $g(Y|D, M, C)$. We further break the total unit treatment, τ_i , into two components: causal mediation effects, $\delta_i(D)$, and direct effects, $\zeta_i(D)$.

The direct effects of treatment capture the change in child health arising from a change in

drought exposure – see equation (2) – for each drought exposure status. The term $W_i(D_i)$ captures an underlying second equation that relates the mediator to a drought conditions, as well as the remaining confounders.

$$\zeta_i = Y_i(D_i = 1, W_i(D_i), C_i) - Y_i(D_i = 0, W_i(D_i), C_i) \quad (2)$$

The mediation effects capture the change in child health arising from a change in the mediator arising from a change in drought exposure – see equation (3) – for all drought exposures. The primary assumption for the effects to be estimated is sequential ignorability (Imai, Keele, and Tingley 2010). It contains two components, strong ignorability (as commonly assumed in propensity score matching) and mediator ignorability (given observed treatment and pre-treatment confounders). The term $W_i(D_i = d)$ represents the fitted relationship between W_i , D_i and C_i evaluated at either $d = \{0, 1\}$.

$$\delta_i = Y_i(D_i, W_i(D_i = 1), C_i) - Y_i(D_i, W_i(D_i = 0), C_i) \quad (3)$$

Strong ignorability is reasonable, under the assumption that drought is a random occurrence; we assume it is conditionally random in the analysis. Mediator ignorability is a stronger assumption. We include numerous controls, such as the child’s age in months, the child’s birth order and gender, the mother’s age, all of which are determined at the time of the child’s birth, and, therefore, it is reasonable to treat them as pre-treatment confounders. However, the total number of children ever born and/or children under the age of five in the household may change, and, therefore, we do not include them in the analysis.

Finally, total unit treatment is the difference in the outcome across drought status, where drought status is assumed to affect the mediator, as in equation (4). Furthermore, it is represented by the treatment weighted average of the two separate effects. The decomposition shows that the proportion of the effect that is mediated is the ratio δ/τ .

$$\begin{aligned}\tau_i &= Y_i(D_i = 1, W_i(D_i = 1), C_i) - Y_i(D_i = 0, W_i(D_i = 0), C_i) \\ &= \delta_i(D_i) + \zeta_i(1 - D_i)\end{aligned}\tag{4}$$

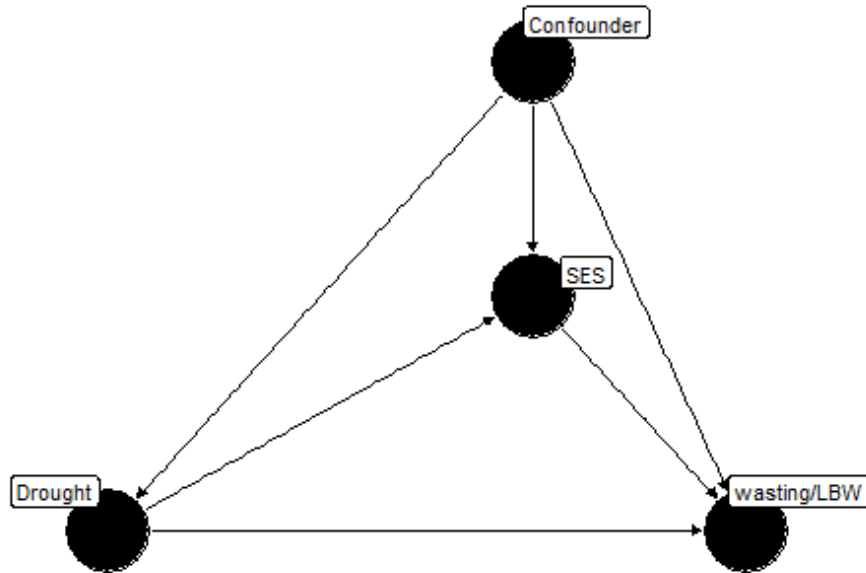


Figure 2.2: Mediation Illustration

To estimate and examine the extent of mediation - we use the `mediation` package in R. The confidence intervals for the treatment parameters are derived from 10 000 nonparametric bootstrap replications. We use the 95% confidence band, by determining the 2.5th and 97.5th percentiles of the bootstrapped treatment parameters described above.

2.6 Results

We begin by describing the main features of the data, we then move to the main results and sensitivity analysis and we conclude with the potential for mediation.

Table 2.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Mother age	10,492	28.994	6.756	15	49
Mother years of education	10,492	5.268	4.055	0	17
Children ever born	10,492	4.217	2.440	1	15
Children under 5 Child	10,492	1.963	0.867	0	7
Mother Height	5,079	159.720	6.110	135.300	191.800
Mother Weight	5,085	55.976	10.609	33.500	165.500
Weight for Height z score score	10,492	-0.229	1.181	-4.970	4.760
Weight for Age z score score	10,492	-0.905	1.142	-5.190	4.420
SPI	10,492	-0.065	0.688	-2.165	2.830
Moderate Drought (0-4 years)	10,492	0.074	0.111	0.000	0.667
Severe Drought (0-4 years)	10,492	0.013	0.046	0.000	0.500
Drought in utero	10,492	0.016	0.126	0	1
Drought in birth year	10,492	0.019	0.137	0	1

2.6.1 Descriptive statistics

Descriptive information is presented in Table 2.1. On average, our mothers have limited education, only about five years, but have an average of 4 children ever born, two of which are under the age of 5. In terms of age, mothers are approximately 29 years, while children are slightly more than two years old. In terms of child health, we see negative averages, implying that our children are shorter and lighter than expected, given their ages. In terms of weight, the average is nearly one standard deviation below the expectation. The World Health Organisation (World Health Organization 2008), uses a z score of two standard deviations below 0 to define underweight, while overweight is based on two standard deviations above the reference population. As expected, given the means, the distribution of WAZ for children aged 0 to 59 months is mainly to the left of center (0), demonstrating that underweight is prevalent among children in Kenya – see Figure 2.3.

Further, the table shows that on average, individuals spend 7.4% of their lives from conception to age four in a moderate drought; here that is defined as an $SPI \leq -1$ and approximately 1.3% in a severe drought with an $SPI < -1.5$ between conception to and including

age four. Figure 2.1 illustrates the SPI from 1965-1999 and highlights rainfall variability over that period.

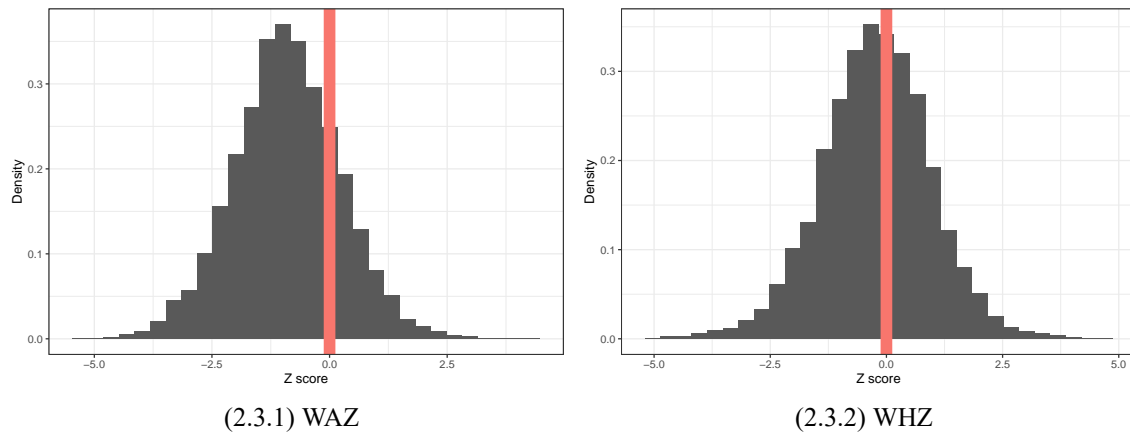


Figure 2.3: Weight for age z-score (WAZ) and weight for height z-score (WHZ)

2.6.2 Overall estimates

First generation analysis

We estimate linear models to investigate the effect of cumulative drought on long-term outcomes for mothers using Ordinary Least Squares (OLS) with standard errors clustered at the household level. Table 2.2 presents the impact of several drought measures, the cumulative drought with an SPI less than -1.5 (for the period $t:t + 4$ and $t - 1:t + 4$) which indicates the impact of severe drought on mothers' SES and health. We start in Model 1 with a specification that includes mother's age, year of birth and district of residence fixed effects. Model 2 add the mother's religion, in the last column, Model 3, we also control for ethnicity. Overall, the results show a negative impact of early life exposure to drought on adult outcomes. The consistent reduction in coefficient magnitude across specifications reflects the inclusion of additional control variables that account for confounding factors. This pattern suggests that the more fully specified models provide more accurate and conservative estimates of the relationships of interest.

According to our results, in Model 3, for every one-unit increase in cumulative drought from *in-utero* up to 4 years, wealth and years of schooling decrease by 0.513 and 2.870 respectively when the SPI is less than -1.5. Both coefficients are statistically significant. We also examine the impact of a less severe drought, using an alternative threshold, when SPI is less than -1, we observe that wealth and education decrease by 0.304 and 1.139, respectively in Model 3. These coefficients are significant at the 1% level. Taken together, the results suggest that the decrease in the wealth index and number of years of schooling is more pronounced when drought becomes more severe. These findings are expected and align with Maccini and Yang (2009), Hyland and Russ (2019), Yamashita and Trinh (2022), Weldeesenbet (2022) who find that weather shocks affect adult outcomes. For instance, Hyland and Russ (2019) observe that drought experienced in childhood decreases the wealth index and years of schooling by 0.035 and 0.449 respectively over 19 countries in Sub-Saharan Africa while Weldeesenbet (2022) find that in Tanzania, drought in birth year reduces the asset index by 0.490 and years of schooling by 1.573.

Apart from analysing the long-term impact of exposure to cumulative drought on socio-economic outcomes, we also test the effects of drought shocks occurring during childhood on mothers weight and BMI. The findings in Table 2.3 show that mothers who experienced cumulative drought of SPI <-1.5 during their infancy are lighter and have an increased likelihood of being underweight (BMI <18.5) as adult. For SPI less than -1.0, we observe a similar trend. These coefficients are statistically significant at the 1% level. The results concur with Shuaihua Song et al. (2024) who find that exposure to famine in childhood has an impact on an individual's BMI in adulthood.

Intergenerational transmission of drought

In this section we analyse the long-term effects of exposure to drought on offspring: We examine the likelihood that a woman who experienced drought in early life will have a child who is underweight or wasted, or born with a low birthweight. We further explore the

Table 2.2: Long term effects of drought on socioeconomic outcomes

	Model 1	Model 2	Model 3
Panel A: Wealth			
Cumulative severe drought ($t - 1 : t + 4$)	-1.6502 ^a (0.202)	-1.4140 ^a (0.195)	-0.5125 ^a (0.155)
Cumulative severe drought1 ($t : t + 4$)	-1.3048 ^a (0.190)	-1.1092 ^a (0.184)	-0.3526 ^c (0.144)
Cumulative moderate drought ($t - 1 : t + 4$)	-0.8942 ^a (0.080)	-0.7563 ^a (0.076)	-0.3036 ^a (0.064)
Cumulative moderate drought1 ($t : t + 4$)	-0.7991 ^a (0.073)	-0.6876 ^a (0.069)	-0.2810 ^a (0.057)
Panel B: Education			
Cumulative severe drought ($t - 1 : t + 4$)	-8.8359 ^a (1.059)	-7.5574 ^a (1.017)	-2.8699 ^a (0.778)
Cumulative severe drought1 ($t : t + 4$)	-7.0061 ^a (0.999)	-5.9422 ^a (0.957)	-1.9959 ^b (0.728)
Cumulative moderate drought ($t - 1 : t + 4$)	-4.3207 ^a (0.467)	-3.5629 ^a (0.456)	-1.1392 ^a (0.394)
Cumulative moderate drought1 ($t : t + 4$)	-3.7746 ^a (0.419)	-3.1588 ^a (0.406)	-0.9977 ^b (0.358)

Severe drought is defined as an SPI < -1.5 and moderate drought to an SPI < -1 . Dependent variables are wealth and education; cluster robust standard errors (clustered at household level) are in parentheses. All estimates are for rural mothers. Model 1 includes Mother's age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity. The subscripts a, b, c, and d denote statistical significance at the 0.005, 0.01, 0.05, and 0.1 levels, respectively

long-term effects of drought on the sex ratio. Since the impacts of drought on children's anthropometrics may vary by gender if households selectively discriminate between boys and girls in the allocation of resources, such as clean water, food, or medical care (M. D. Gupta 1987; R. Gupta et al. 2016; Koohi-Kamali 2008). Thus, we separately estimate our model by gender to examine the potential difference in the long-term impact of drought for boys and girls. We use cumulative and single drought measures, drought in the year of birth and first year of life, to capture this impact. The gender-specific results are presented in Tables 2.4, 2.5, 2.6. Overall, there is an increased likelihood for a child to be underweight if the mother has experienced drought in her infancy but the impact is greater and significant

Table 2.3: Long term effects of drought on weight and BMI outcomes

	Model 1	Model 2	Model 3
Panel A: Weight			
Cumulative severe drought ($t - 1 : t + 4$)	-12.5185 ^a (4.117)	-11.4865 ^b (4.140)	-6.1081 (3.816)
Cumulative severe drought1 ($t : t + 4$)	-10.2638 ^b (3.825)	-9.5248 ^c (3.822)	-4.7246 (3.480)
Cumulative moderate drought ($t - 1 : t + 4$)	-7.7897 ^a (2.068)	-7.4178 ^a (2.080)	-4.4499 ^c (2.051)
Cumulative moderate drought1 ($t : t + 4$)	-6.7822 ^a (1.680)	-6.4984 ^a (1.688)	-3.9992 ^c (1.665)
Panel B: BMI < 18.5			
Cumulative severe drought ($t - 1 : t + 4$)	0.5823 ^a (0.180)	0.5306 ^a (0.179)	0.3378 ^c (0.169)
Cumulative severe drought1 ($t : t + 4$)	0.4549 ^b (0.165)	0.4179 ^c (0.164)	0.2426 (0.154)
Cumulative moderate drought ($t - 1 : t + 4$)	0.2818 ^a (0.067)	0.2619 ^a (0.067)	0.1181 ^d (0.068)
Cumulative moderate drought1 ($t : t + 4$)	0.2475 ^a (0.062)	0.2325 ^a (0.061)	0.1058 ^d (0.063)

Severe drought is defined as an SPI < -1.5 and moderate drought to an SPI < -1. Dependent variables are weight and BMI; cluster robust standard errors (clustered at household level) are in parentheses. All estimates are for rural mothers. Model 1 includes Mother's age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity. The subscripts a, b, c, and d denote statistical significance at the 0.005, 0.01, 0.05, and 0.1 levels, respectively

for boys compared to girls. These results are consistent with Abiona (2024) who finds that short-term shocks are more likely to affect girls than boys; On the other hand, the results of long term impact on underweight (Table 2.4 and stunting (Table B.1 are mixed and mostly not significant. Table 2.6 shows that long-term drought affects the sex ratio, leading to a higher likelihood that mothers experiencing adverse conditions will give birth to more girls than boys. This finding is consistent with the work of Thouzeau et al. (2023) and Trivers and Willard (1973) who find that individuals with poor health and economic outcomes are more likely to give birth to daughters later in life while their sons born face higher mortality rates within the first year of life. In addition, our results of the long-term impact of drought

on low birth weight in Table B.2 indicates an increased likelihood of low birthweight among boys although not significant. These findings aligns with existing research suggesting that male fetuses are more susceptible to prenatal stressors compared to female fetuses as they might struggle more than female children because they are not as well-equipped as girls to cope with adverse conditions in the womb, making them more dependent on maternal nutritional flow (Kraemer 2000; Currie and Schwandt 2016; Clark, D’Ambrosio, and Rohde 2021; Abiona 2024).

Table 2.4: Long-term impacts of drought on child underweight indicator

	Model 1	Model 2	Model 3
Panel A: Females			
Cumulative severe drought ($t - 1 : t + 4$)	0.0218 (0.022)	0.0220 (0.022)	0.0164 (0.020)
Cumulative severe drought1 ($t : t + 4$)	0.0140 (0.022)	0.0142 (0.022)	0.0097 (0.020)
Cumulative moderate drought ($t - 1 : t + 4$)	-0.0082 (0.012)	-0.0083 (0.012)	-0.0096 (0.013)
Cumulative moderate drought1 ($t : t + 4$)	-0.0048 (0.011)	-0.0049 (0.011)	-0.0059 (0.012)
Panel B: Males			
Cumulative severe drought ($t - 1 : t + 4$)	0.0280 ^a (0.008)	0.0260 ^a (0.008)	0.0253 ^a (0.008)
Cumulative severe drought1 ($t : t + 4$)	0.0228 ^a (0.007)	0.0212 ^a (0.007)	0.0205 ^a (0.006)
Cumulative moderate drought ($t - 1 : t + 4$)	0.0166 ^c (0.007)	0.0152 ^c (0.006)	0.0137 ^c (0.007)
Cumulative moderate drought1 ($t : t + 4$)	0.0139 ^c (0.006)	0.0127 ^c (0.006)	0.0112 ^d (0.006)

Severe drought is defined as an SPI < -1.5 and moderate drought is an SPI < -1 . Dependent variable is underweight; cluster robust standard errors (clustered at household level) are in parentheses. All estimates are for rural mothers. Model 1 includes Mother’s age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity. The subscripts a, b, c, and d denote statistical significance at the 0.005, 0.01, 0.05, and 0.1 levels, respectively

Table 2.5: Long term impact of drought on child stunting

	Model 1	Model 2	Model 3
Panel A: Females			
Cumulative severe drought ($t - 1 : t + 4$)	0.0499 (0.040)	0.0555 (0.040)	0.0753 ^d (0.044)
Cumulative severe drought1 ($t : t + 4$)	0.0153 (0.040)	0.0195 (0.040)	0.0242 (0.041)
Cumulative moderate drought ($t - 1 : t + 4$)	-0.0096 (0.019)	-0.0071 (0.019)	0.0004 (0.019)
Cumulative moderate drought1 ($t : t + 4$)	-0.0134 (0.018)	-0.0115 (0.018)	-0.0055 (0.018)
Panel B: Males			
Cumulative severe drought ($t - 1 : t + 4$)	-0.0103 (0.044)	-0.0115 (0.044)	-0.0018 (0.044)
Cumulative severe drought1 ($t : t + 4$)	-0.0395 (0.045)	-0.0404 (0.045)	-0.0273 (0.043)
Cumulative moderate drought ($t - 1 : t + 4$)	-0.0071 (0.016)	-0.0078 (0.016)	0.0027 (0.017)
Cumulative moderate drought1 ($t : t + 4$)	-0.0026 (0.014)	-0.0031 (0.014)	0.0072 (0.014)

Severe drought is defined as an SPI < -1.5 and moderate drought is an SPI < -1 . Dependent variable is stunting; cluster robust standard errors (clustered at household level) are in parentheses. All estimates are for rural mothers. Model 1 includes Mother's age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity. The subscripts a, b, c, and d denote statistical significance at the 0.005, 0.01, 0.05, and 0.1 levels, respectively

2.6.3 Indirect drought effects on child health via Socioeconomic status (SES) variables

Next, we turn to potential mechanisms mediating between drought and child health. In most large-scale quantitative analyses of weather and health, it is not always possible to test such mechanisms, due to data limitations (Phalkey et al. 2015; Randell, Gray, and Grace 2020). In this study, we estimate the impact of SES as a mechanism through which drought might affect child health. We do so using two variables from the DHS survey, namely, wealth index and total years of formal schooling.

Table 2.6: Long term impact of drought on child sex ratio

	Model 1	Model 2	Model 3
Cumulative severe drought ($t - 1 : t + 4$)	-0.1474 (0.111)	-0.1364 (0.112)	-0.1544 (0.119)
Cumulative severe drought1 ($t : t + 4$)	-0.1379 (0.103)	-0.1291 (0.104)	-0.1175 (0.106)
Cumulative moderate drought ($t - 1 : t + 4$)	0.0031 (0.047)	0.0101 (0.047)	0.0171 (0.048)
Cumulative moderate drought1 ($t : t + 4$)	0.0099 (0.042)	0.0155 (0.043)	0.0225 (0.043)

Severe drought is defined as an $SPI < -1.5$ and moderate drought is an $SPI < -1$. Dependent variable is sex ratio; cluster robust standard errors (clustered at household level) are in parentheses. All estimates are for rural mothers. Model 1 includes Mother's age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity. The subscripts a, b, c, and d denote statistical significance at the 0.005, 0.01, 0.05, and 0.1 levels, respectively

We present the results related to underweight in Table 2.7, which contains four panels: the first two focus on mediation through the wealth index while the last two focus on mediation through the lack of education. In each panel, we see the ACME (average causal mediation effects), ADE (average direct effects), total effects and the proportion (prop.) mediated. Recall from the methods section, equations (3) – (4), which highlight the definitions for ACME, ADE and total effect, as well as the proportion mediated.⁶ In addition to the estimates, confidence intervals based on 10 000 nonparametric bootstrap replications are presented, along with the implied p-value from a simple test of statistical significance.

The results of the analysis are consistent and expected. Firstly, given the focus on underweight in Table 2.7, the total are expected to be the same for each drought type. The main difference between the panels comes through mediation, as well as the difference in drought severity. Secondly, the likelihood of being underweight is higher for children

⁶The ACME captures the change in child health arising from a change in the mediator arising from a change in drought exposure. It is estimate from a model that includes the variables implied by all nodes in Figure 2.2: W_i , D_i , and C_i . The ADE, on the other hand, focuses on a model that does not include the possible path through water insecurity, i.e., it is estimated from a model that does not include W_i .

whose mothers were affected by drought, as shown in the table. Thirdly, mediation effects for the wealth index are statistically significant, positive and relatively larger for the severe drought comparatively to moderate drought. Similarly, the mediation effects for education are also statistically significant. The mediated proportion in severe drought is similar for the wealth index and education.

Since the mediation analysis for wealth and education is statistically significant, it means that these variables play a meaningful intermediary role in the relationship between the initial exposure to drought by the mothers and the health outcomes of their children. In other words, part of the effect of the exposure on health operates through changes in wealth and education. This helps us understand the underlying pathways or mechanisms-suggesting that impacts on socioeconomic status may be key channels through which climate variability impacts health in the next generation.

2.7 Robustness checks

In this section, we discuss some sensitivity analysis based on alternative specifications of drought, testing the validity of the results described in the previous sections. We consider drought as a single shock in the year of birth and the year after birth, respectively. We further test the long-term impact of a shorter period of cumulative droughts, from *in utero* up to 2 years of life. Thus, we estimate the model using different drought measures to ensure that the results are not driven by our choice of the year in which the drought occurred or the length of the cumulative drought exposure.

Table 2.8 presents results based on drought being a single shock in the year of birth or in the first year of life. The results are similar to those in our primary analysis, although smaller in magnitude. Again, drought is negatively associated with adult outcomes. These findings demonstrate that the length of the exposure does not influence our main conclusions, although it does alter the magnitudes. We also estimate a model with a reduced cumulative

Table 2.7: Indirect effects of drought on underweight through SES

	Estimate	95% CI Lower	95% CI Upper	p-value
Panel A: Wealths in severe drought				
Mediation	0.002	0.001	0.004	0.0
Direct	0.018	0.003	0.032	0.0
Total	0.021	0.006	0.035	0.0
Propotion	0.103	0.066	0.502	0.0
Panel B: Wealths in moderate drought				
Mediation	0.001	0.001	0.002	0.0
Direct	0.002	-0.011	0.014	0.8
Total	0.003	-0.010	0.016	1.0
Propotion	0.440	-2.020	0.966	1.0
Panel C: Education in severe drought				
Mediation	0.002	0.001	0.002	0.0
Direct	0.019	0.005	0.034	0.0
Total	0.021	0.006	0.035	0.0
Propotion	0.077	0.034	0.292	0.0
Panel D: Education in moderate drought				
Mediation	0.001	0.000	0.001	0.0
Direct	0.002	-0.010	0.019	0.6
Total	0.003	-0.009	0.019	0.4
Propotion	0.222	-0.071	1.437	0.4

Note. Mediation is the average causal mediation effect, Direct is the average direct effect of drought. Total is the sum of the two. Proportion is the share of the total that is estimated to be mediated by SES.

drought exposure period *in utero* period up to 2 years. We include results from SPI less than -1.5 (severe cumulative drought). We find a negative and statistically significant effect of cumulative drought on wealth and years of schooling however, the magnitudes are close to those estimated across all years. Thus, we find additional support for our main findings on the long-term impact of drought on socioeconomic conditions later in life, although the estimates do not support the hypothesis that the impact of weather events is more prominent during the first two years of life.

Table 2.8: Long term effects of alternative measures of drought on socioeconomic outcomes

	Model 1	Model 2	Model 3
Panel A: Wealth			
Drought in utero	-0.2798 ^a (0.057)	-0.2434 ^a (0.055)	-0.1182 ^c (0.048)
Drought in birth year	-0.2913 ^a (0.062)	-0.2678 ^a (0.062)	-0.0658 (0.046)
Drought in first year	-0.3026 ^a (0.093)	-0.2877 ^a (0.093)	0.0330 (0.066)
Cumulative moderate drought ($t - 1 : t + 2$)	-1.1096 ^a (0.144)	-0.9558 ^a (0.141)	-0.2787 ^c (0.113)
Panel B: Education			
Drought in utero	-1.4836 ^a (0.325)	-1.2910 ^a (0.316)	-0.6469 ^b (0.231)
Drought in birth year	-1.7221 ^a (0.330)	-1.6179 ^a (0.326)	-0.4624 ^d (0.249)
Drought in first year	-1.6318 ^a (0.508)	-1.5875 ^a (0.489)	0.1232 (0.333)
Cumulative moderate drought ($t - 1 : t + 2$)	-6.2807 ^a (0.762)	-5.4557 ^a (0.737)	-1.8150 ^a (0.549)

Severe drought defines an SPI < -1.5 and moderate is an SPI < -1 . Cluster robust standard errors (clustered at household level) are in parentheses. All estimates are for rural mothers. Model 1 includes Mother's age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity. The subscripts a, b, c, and d denote statistical significance at the 0.005, 0.01, 0.05, and 0.1 levels, respectively

2.8 Discussion

Our findings indicate that early childhood exposure to drought conditions can have enduring and significant impacts. Specifically, we observe that the socioeconomic status of women in rural households is influenced by the weather conditions they encountered decades earlier. Thus, early-life drought exposure is strongly linked to lesser wealth and lower educational attainment. Our findings that droughts influence adult socioeconomic status (wealth), education attainment and health agrees with several studies in the literature Chang, Favara, and Novella (2022). There are potential channels through which short-term rainfall deficits may affect child health with consequences in the long run. The climate-health literature has

broadly identified two mechanisms linking weather conditions to child health: agricultural outcomes and infectious disease transmission. Specifically, drought reduces household income through decreased crop and livestock production, negatively affecting child nutrition (Carpena 2019; Amondo, Nshakira-Rukundo, and Mirzabaev 2023), while favorable rainfall improves household income, child nutrition, and health. The second pathway is the proliferation of infectious diseases, which might result from rainfall deficit and excess rainfall. Droughts and excessive rainfall affect the environment and lead to an increase in diarrhea, vector-borne illnesses, and/or waterborne diseases, which are detrimental to both young children and pregnant women (Rabassa, Skoufias, and Jacoby 2014; Omiat and Shively 2020).

Nevertheless, previous literature has generally focused on either the long-term or short-term impacts of weather-related shocks, without exploring the effects on the next generation. Our results on the intergenerational effects of drought show that for women who experienced droughts in their earliest years, the impacts are not only felt in the long term but are transmitted to their children. They suggest an increase in the likelihood of having *underweight... stunted* and wasted children or giving birth to low birth weight child. These findings concur with Hyland and Russ (2019) who observe long-term impact of drought on birth weight as well as Abiona and Ajefu (2023) and Randell, Gray, and Grace (2020) who document the short-term effects of rainfall deficit on child anthropometrics.

The literature highlights several consequences associated with poor child health as these conditions are linked to adverse short and long-term outcomes such as high infant mortality, cerebral palsy, blindness, hypertension and coronary diseases later in life; they have also been linked to adverse socio-economic outcomes such as poor cognitive skills and lower intelligence quotient (IQ) in childhood, reduced employment and earnings later in adulthood (Almond, Chay, and Lee 2005; Camacho 2008; Cutland et al. 2017; Kirkegaard et al. 2020; Soliman et al. 2021; Bougma et al. 2022), thus, creating a vicious cycle that extends across multiple generations (Hyland and Russ 2019).

In addition, our findings on the long-term impact of droughts on sex ratio suggest that women who experienced droughts decades ago have an increased likelihood of having more girls than boys in line with Thouzeau et al. (2023), Almond et al. (2010), Almond and Edlund (2007) and Trivers and Willard (1973) who observed that parental condition affects offspring. Specifically, individuals with poor health and economic outcomes are more likely to give birth to daughters later in life while sons born to disadvantaged mothers face higher mortality rates within the first year.

The intergenerational impacts of weather related shocks may be transmitted to the next generation through various mechanisms including biological or epigenetics, social and behavioural. It is not always possible to directly test these mechanisms, due to data limitations (Phalkey et al. 2015; Randell, Gray, and Grace 2020). However, we attempt to estimate the mediation effect of Socioeconomic Status (SES) captured by two variables – wealth and education – using a simple mediation analysis (path analysis). We find that drought decreases wealth as well as the years of formal schooling, which in turn adversely impacts child health by increasing the likelihood of stunting, wasting and low birth weight. The indirect effects of SES seem to mediate the long-term effects of drought on child health in rural Kenya. The results are in line Houweling and Grünberger (2024) and Aizer (2019) which emphasizes the importance of parental SES in shaping a child’s health trajectory and perpetuating socioeconomic inequalities in adulthood.

2.9 Conclusion

Climate change is predicted to exacerbate water scarcity even further through reductions in precipitation and increases in evapotranspiration rates. Early childhood is a critical period as children are more susceptible to the health dangers related to undernutrition, due to the intense nutrient requirements underlying their physiological development with consequence in later life such as reduced cognitive development and increase risk of developing chronic

health conditions, amongst others, which are likely to influence both educational attainment and employment prospects. Moreover, these long term outcomes are transmitted to future generations. Thus, understanding the impact of climate and weather on short and long term outcomes is relevant from a development perspective.

For this research, we merge data from the 2014 Kenya Demographic and Health Surveys and climate data from the Climate Research Unit's Time-Series. We compute the Standardised Precipitation Index (SPI) for each district per year using the monthly precipitation series from 1950-2014, to construct a cumulative measure of drought exposure in a woman's earliest life. We then investigate the impacts of rainfall fluctuations on long-term socioeconomic and health outcomes among women in rural Kenya. Our results show that early life exposure to drought adversely affects socioeconomic status later in life. We, then, explore the intergenerational effects of maternal drought exposure on offspring. We find that mothers who experienced drought conditions decades earlier are more likely to give birth to daughters, have sons with low birthweight, and have sons who are underweight during childhood.

Furthermore, we use mediation analysis to investigate whether socioeconomic status (SES) is a mechanism through which the impacts of drought are transmitted to the next generations. We capture SES through a wealth index and years of formal school. Our results provide evidence that indirect effects related to SES mediate the relationship between climate variability and child health.

In the developing world, particularly in arid and semi-arid land, drought is a significant problem for many in the population. This phenomenon will likely be compounded by climate change as the planet warms up, temperatures increase, and precipitation levels vary around the globe. Thus, there is a need for interventions that build the resilience of communities in regions prone to climate stress, to break cycles of intergenerational health inequalities and ensure that future generations are not disproportionately affected.

3 CHAPTER 3 Can Rainfall serve as a Remedial Investment for Low Birth Weight Children?

3.1 Introduction

Around the world, low birth weight (LBW) is a major public health problem with subsequent short and long-term impacts. LBW represents about 15.5 percent of all live births, with more than 90 percent occurring in developing countries (United Nations Children's Fund (UNICEF) 2019). A strand of the research finds a strong relationship between LBW and adverse health conditions such as high infant mortality, cerebral palsy, blindness, hypertension, coronary diseases later, and LBW has also been related to adverse socio-economic outcomes such as poor cognitive skills and lower intelligence quotient (IQ) in childhood, reduced employment and earnings later in life (Almond, Chay, and Lee 2005; Camacho 2008; Cutland et al. 2017; Kirkegaard et al. 2020; Soliman et al. 2021; Bougma et al. 2022).

Therefore, remediation or catch-up growth is crucial for LBW children to thrive and reach their full potential in life. Catch-up growth refers to improved anthropometric outcomes, namely weight, and height, from an initial disadvantage (Anand et al. 2018). This study seeks to answer the question of whether catch-up growth is possible for LBW children and what are the factors that contribute to catch-up growth. We focus specifically on positive rainfall shock as a remedial investment since, in an agrarian context with rainfed agriculture, favorable rainfall is a beneficial event that might contribute to catch-up growth. We leverage the exogeneity of the rainfall variable to isolate the variation in exposure to other determinants of catch-up growth because unobserved parental investments and genetic potential could lead to biased and inconsistent estimates (Outes and Porter 2013; Adhvaryu et al. 2023). Moreover, we contribute to understanding the other factors associated with catch-up growth incidence, such as maternal height, education, and economic status.

Closely linked to remediation is the notion of critical periods. There is a debate in the literature concerning the period during childhood which is more sensitive to catch-up growth and yields the most considerable returns. Some researchers argue that investing in children at a very young age provides the highest returns to investment (Cunha, Heckman, and Schennach 2010; Heckman, Pinto, and Savelyev 2013) and that catch-up from nutritional deficiencies is reduced after the child's second birthday (Victora et al. 2010). However, recent work suggests a possibility of achieving catch-up on both physical and cognitive dimensions after age two (Hirvonen 2014; Lundeen et al. 2014; Adhvaryu et al. 2023). We further this discussion by measuring catch-up growth at ages two and four years to determine if catch-up continues after the first two years of life. We use both the absolute and relative definitions of catch-up growth in weight.

Few studies in economics sought to quantify catch-up growth. However, estimates of catch up growth differ due to the definitions and metrics used. The various definitions are summarised into absolute (raw) and relative catch-up growth (Desmond and Casale 2017). Absolute catch-up growth occurs if the absolute weight deficit in kg decreases over time, in other words, if the Weight for Age Difference (WAD) declines (Leroy et al. 2015). Relative definitions refer to catch-up growth as an improvement in the Weight for Age Z (WAZ) scores, they are more commonly used in the literature (Casale, Desmond, and Richter 2020; Anand et al. 2018; Victora et al. 2010; Outes and Porter 2013; Desmond and Casale 2017). In this chapter, we use the Kenya 2014 DHS dataset to investigate catch up growth in terms of both WAZ and WAD in LBW children.

The study results indicate that there is catch-up growth in weight from one to four years. This suggests that LBW children can achieve nutritional catch-up after their second birthday (Casale, Desmond, and Richter 2020; Outes and Porter 2013). This catch-up growth is observed in both absolute (WAD) and relative (WAZ) definitions. In addition, although results are not highly statistically significant, the findings suggest that exposure to positive rainfall during childhood may be associated with an increased likelihood of catch-up

growth in weight along side other factors. These results are in line with other studies in economics on the role of interventions in lessening the adverse impact of disadvantage in early childhood, which highlight the positive role of health interventions, welfare programs, and childcare programs and show that remediation is possible after poor circumstances in early life (Heckman 2011; Heckman, Pinto, and Savelyev 2013; Bharadwaj, Løken, and Neilson 2013; Campbell et al. 2014; Conti, Heckman, and Pinto 2016; Lynch and Gibbs 2017; Aizer 2019; J. L. García et al. 2020).

Hence, we contribute to the literature in three ways. First, we extend the discussion about catch-up growth measurement, as the study analyses whether catch-up growth occurs at ages two and four years using the absolute and relative definitions of catch-up growth in weight. Second, we contribute to the debate in the literature concerning the period during childhood which is more sensitive to catch-up growth and yields the most considerable returns by measuring catch-up growth at ages two and four years to determine if this growth continues after the first two years of life. Third, this study attempts to address the issue of endogeneity associated with the factors that influence catch-up growth. Since catch-up growth involves comparing two different time periods, the relationship between the two nutritional periods may be affected by endogeneity concerns. This is because outcomes and investments are influenced by the preferences of parents and the resources available to families (Adhvaryu et al. 2023). Furthermore, unobserved parental investments and genetic potential could also lead to biased and inconsistent estimates of catch up growth (Outes and Porter 2013). Thus, we exploit the exposure to rainfall as a quasi-random and exogenous event to achieve plausibly better estimates of catch up growth for LBW children. we explore whether positive rainfall helps generate catch-up growth in weight in LBW children in developing countries where interventions to remediate adverse early life conditions are scarce. We leverage the fact that in Arid and semi-arid lands (ASALs), positive rainfall is a beneficial event, and also, in an agrarian setting with rainfed agriculture such as Kenya, weather plays a crucial in determining households income and nutrient intake, which in

turn have implications for children's health. We also analyse the impacts of other factors on catch-up growth.

The remainder of the chapter is organized as follows: Section 2 provides a brief literature review. Section 3 discusses the data, while section 4 covers the empirical strategy. Section 5 presents the descriptive statistics and the results of the various estimations. Section 6 covers the discussion.

3.2 Literature

The critical importance of the first 1000 days of life, in utero period included, and how adverse conditions experienced during this period can negatively affect life outcomes, including educational attainment, adult employment, and earnings is established as well as the need for catch up growth. (Alderman, Hoddinott, and Kinsey 2006; Deschênes, Greenstone, and Guryan 2009; Almquist 2016; Rosales-Rueda 2018; Thiede and Strube 2020). Research suggests possible remediation for growth faltering in early childhood (Heckman 2011; Aizer 2019), but while the importance of child growth is well established, it is equally important to determine the interventions and factors that contribute to catch up growth. In doing so, we first investigate if positive rainfall shocks help LBW children to catch up and also which period during childhood is more sensitive to catch-up growth and yields the highest returns.

Prader, Tanner, and Harnack (1963) referred to the term catch-up growth, which describes a period of acceleration in growth in response to recovery from illness or starvation. Some researchers suggest that the term catch-up growth is mainly used for height, defined as height velocity above normal following a transient period of growth inhibition (Boersma and Wit 1997; Wit 2002; Casale, Desmond, and Richter 2020). However, other researchers extend the catch-up growth concept to include weight recovery (Williams 1981; Fernandes et al. 2019; Cooke et al. 2023) or a physiologic increase in Weight-For-Age z score after a

period of growth faltering, ideally to the original growth trajectory. This study focuses on catch-up in weight for LBW children because weight increase is vital for the appropriate management of LBW children (Sivakumar, Arunprasath, and Ramanan 2021). The Kenya DHS datasets provide weight observations at two points in time, namely at birth and during the year of the survey which allow us to estimate catch-up growth.

In recent years, researchers in economics have sought to quantify catch-up growth using diverse analysis methods that differ on the definition of metrics used. For instance, Hoddinott and Kinsey (2001); Victora et al. (2010); Outes and Porter (2013) estimate catch-up growth by regressing Height for Age z scores (HAZ) in the second period (pre-adolescence or adulthood) on the first period HAZ (early childhood). The coefficient of the lagged HAZ represents the catch-up growth. Some authors use changes in height as the dependent variable. These approaches are criticized in the literature (Hirvonen 2014; Lundeen et al. 2014; Leroy et al. 2015; Frongillo, Leroy, and Lapping 2019). Leroy et al. (2015) define catch-up growth as a reduction in absolute weight/height deficit (kg, cm) that occurs in the Weight for Age Difference (WAD)/Height for Age Difference (HAD) and demonstrate that conclusions of catch-up growth based on the z scores are inappropriate as the z scores are not useful tools to assess changes over time. This is because anthropometric z scores are constructed by dividing the WAD/HAD by the Standard Deviation. Therefore, changes in the z scores could be difficult to interpret since these changes can stem from changes in the numerator, denominator, or both. Desmond and Casale (2017) summarise the various metrics into absolute and relative definitions of catch-up growth captured by WAD/HAD and WAZ/HAZ respectively and show that estimates based on positive changes in both types of definitions differ. In this study, using both definitions of catch-up growth, absolute and relative, we find different rates of catch-up growth among LBW children: catch-up growth percentages measured using absolute metrics were lower than those measured using relative metrics.

Over the past decade, researchers have documented a reduced likelihood of catch up growth

after two years of age suggesting that investing in children at a very young age provides the highest returns to investment (Cunha, Heckman, and Schennach 2010; Victora et al. 2010; Heckman 2011). Nonetheless, recent studies have provided evidence of children with improved anthropometrics in later childhood and possibility of achieving catch-up on both physical and cognitive dimensions after age two (Casale, Desmond, and Richter 2020; Richard et al. 2021).

Furthermore, another strand of the literature in economics analyses the impact of remedial investments and interventions during early life on conditions later in life. Researchers investigate the role of health interventions, welfare programs, and childcare programs (Heckman 2011; Heckman, Pinto, and Savelyev 2013; Bharadwaj, Løken, and Neilson 2013; Campbell et al. 2014; Conti, Heckman, and Pinto 2016; Lynch and Gibbs 2017; Aizer 2019; J. L. García et al. 2020). Roberts and Stein (2017) provide evidence in a systematic review and meta-analysis on the impact of nutritional interventions in 69 studies that zinc and vitamin A are effective in increasing catch-up growth in children above two years old. Aizer (2019) estimate the causal impact of family income on the birth weight in low-income families who benefited from a food stamp program implemented in the U.S. and find a positive impact on birth weight. These studies endeavor to provide evidence that remediation is possible after poor circumstances in early life. However, interventions targeting LBW children in rural Africa are scarce. Therefore, in the context of Arid and semi-arid lands (ASALs) and agrarian settings, we investigate whether positive early-life rainfall acts as a remedial investment for LBW children. In other words, we investigate if LBW children with exposure to positive rainfall in infancy experience catch-up growth in weight.

Beside remedial interventions, there are other factors associated with catch-up growth. Several studies find that household socioeconomic status might influence catch-up growth: children living in relatively richer or less credit-constrained households tend to achieve higher catch-up growth compared to their counterparts in poor households (Almond and Currie 2011; Outes and Porter 2013); environmental factors such as access to clean drink-

ing water, improved sanitation and hygiene practices (Shrestha, Vicendese, and Erbas 2020) and whether a child resides in an urban or rural area - also play a role. Biological and child-specific characteristics, including birth weight, sex, and birth order have been shown to affect catch-up growth. Parental characteristics such as mother education (Siddiqa et al. 2023) and parental anthropometry such as birth weight, adult height, and body mass index are also associated with offspring birth size (Addo et al. 2015). However, the relationship between early and later nutritional periods might suffer from endogeneity concerns as resulting outcomes and investments are shaped by the preferences of parents and access to resources by families that might lead to biased and inconsistent estimates (Outes and Porter 2013; Adhvaryu et al. 2023). The findings of this study are aligned with the above. We find that mother's age is positively correlated with catch up growth but no significant relationship for education. In addition, economic status, proxied by the wealth index, is positively associated with catch up growth.

Therefore, this study analyses whether catch-up growth happens at ages 2 and 4 using the absolute and relative definitions of catch-up growth in weight. We find that LBW children experience catch-up at both ages 2 and 4. We further explore if positive early-life rainfall is a remedial investment for LBW children. In other words, we investigate if LBW children exposed to positive rainfall in infancy experience catch-up growth in weight compared to other LBW children with no such exposure. We find that positive rainfall shocks may contribute to catch-up growth of LBW children although the results are mixed. The climate-health research identifies several pathways through which rainfall may impact child growth and health. In the context of developing economies, particularly in Africa, the first channel through which early-life positive rainfall could affect health is agricultural outcomes and nutrient intake. Agriculture employs over 60% of the workforce, and nearly 95% of cropland is rain-fed (Abrams 2018; Africa development Bank 2021). Therefore, favourable rainfall in rural settings tends to improve households income and food security through better crop and livestock (Maccini and Yang 2009; Adhvaryu et al. 2023). Water availability

is another pathway through which positive rainfall may contribute to catch-up growth in weight. Arid and semi-arid regions face water scarcity, which entails regular water collection for consumption, hygiene, and other household needs. For instance, in rural Kenya, individuals spend, on average, 46 minutes fetching water and a maximum of six hours, as the majority of households do not have water on their plots. Thus positive rainfall shocks may increase water security.

3.3 Data

We use data from two main sources in this study. The first is the Kenyan Demographic and Health Surveys (DHS) conducted in 1993, 1998, 2003, 2008, and 2014 which we extract from the Integrated Public Use Microdata Series database, IPUMS-DHS. The Second data source is the gridded weather data from the University of East Anglia Climate Research Unit Time Series (CRUTS) where we extract the rainfall data used to construct the Standard Precipitation Index (SPI) by district by year.⁷ The following sections describe the data in more detail.

3.3.1 Demographic Health Survey (DHS) data

We access data from the DHS through the Integrated Public Use Microdata Series database, IPUMS-DHS (Boyle, King, and Sobek 2024) as described in Chapter 2. In this chapter, we seek to first assess if LBW children catch-up, then we investigate the role of positive rainfall shocks as a remediation intervention for LBW children. Thus, we need information on antropometric data for at least two points in time to compare the weight at birth and the

⁷Data cleaning and preparation is done with Stata version 15.1. For the analysis, we use R version 4.4.1 (R Core Team 2023) with the following packages: `haven` (Wickham 2023) to import foreign statistical formats (mainly Stata) into R; `tidyverse` (Wickham 2023) to import, clean, manipulation, transform and present the data; `stargazer` (Hlavac 2022) for summary statistics table, `knitr` (Xie 2024) for dynamic report generation in R; `modelsummary` (Arel-Bundock 2022) for results tables; `kableExtra` (Travison et al. 2024) to construct complex tables and customize them, as needed; `stats` (Hothorn and Zeileis. 2022) to estimate probit models. We further use `rmarkdown` (@ Allaire et al. 2024) to combine R codes, results from the data analysis and the text into one reproducible document.

weight at any point in time. The DHS provides data on weight at birth and during the year of survey for children aged 0 - 59 months which allow us to assess whether catch-up growth occurs.

To investigate whether catch-up growth occurs for LBW children, we pool data from four rounds of Kenya Demographic and Health Surveys (DHS) conducted in 1993, 1998, 2003, 2008, and 2014. Each round of the survey includes anthropometric data on children and along with information on their mothers and household characteristics. A total of 42,638 observations are included in the pooled dataset constructed from five rounds of the DHS but birth weight is recorded for only 15,657 children. Following the World Health Organization (WHO, n.d.) definition of LBW as a birth weight of less than 2500g, we have 1,186 observations of LBW children. Since the DHS is a cross-sectional survey that captures a snapshot in time and doesn't track the same children over the years, we specifically classify children according to their age from one to four during the year of survey using the variable "kid current age" in years: 1 year (251 observations), 2 years (225 observations), 3 years (209 observations), 4 years (168 observations). This allows us to assess whether catch-up growth occurs up to age two and beyond. However, birth weight data in the DHS are subject to potential bias due to both non-response and misreporting. In contexts like Kenya, where a substantial proportion of births occur outside health facilities, birth weight is often not recorded at birth and must be recalled by the mother. As a result, recall bias may affect the accuracy of reported birth weights, particularly for older children. These limitations may lead to underestimation or overestimation of true associations, and we interpret results accordingly.

To examine the role of positive rainfall shocks on catch-up growth of LBW children, we need to merge sub-administrative rainfall and DHS data. Hence, we focus solely on the 2014 DHS survey because it contains district-level information compared to other DHS rounds, where households in the enumeration areas are grouped by district. This is because Kenya's counties were established in 2010 by the Constitution, replacing the previous eight-

district system. The World Health Organization (WHO) defines low birth weight (LBW) as a birth weight of less than 2,500 grams. In the 2014 Kenya DHS dataset, the number of observations with birth weight strictly below 2,500 grams is relatively small, 387 observations after removing records with missing observations, which limits statistical power. To address this limitation and enhance the robustness of the analysis, we adopt an expanded operational definition of low birth weight that includes all children with a birth weight less than or equal to 2,500 grams. This definition is closest to LBW as defined by UNICEF of less than 2,500 grams (up to and including 2,499 grams)⁸ and consistent with approaches used in related empirical studies such as Schieve et al. (2002). Thus we have 665 observations of birth weight less or equal to 2500 grams. We acknowledge the limitations of using a single survey wave to analyze the effects of rainfall on catch-up growth. However, our approach mitigates some of these concerns in several ways: (i) We match exogenous rainfall variability (as measured by the Standardized Precipitation Index, SPI) to early-life periods of children observed in the survey, the health outcomes are captured at two points in time. This allows us to explore and compare the effects of climate shocks that occurred post to the first period. (ii) Rainfall shocks are plausibly exogenous making them suitable for causal inference, even in cross-sectional settings. Several influential studies in development and health economics (Maccini and Yang 2009; Dinkelman 2017) have used a similar approach showing that weather shocks can be treated as exogenous sources of variation, making them well-suited for causal inference even in non-panel settings. (iii) We incorporate various controls (maternal, child, and household characteristics) and district-level fixed effects to account for unobserved heterogeneity. While panel data would allow for stronger identification, our use of spatially and temporally matched climate data with retrospective health information represents a well-established approach in climate-health economics and development literature.

⁸<https://data.unicef.org/topic/nutrition/low-birthweight/?utm>

3.3.2 Rainfall Data

The monthly rainfall data from the University of East Anglia Climate Research Unit's Time Series (CRUTS). Using the rainfall data, we compute the annual Standardised Precipitation Index (SPI)(McKee, Doesken, and Kleist 1993) using the Princeton package from R. The SPI is obtained by fitting a gamma or a Pearson Type III distribution to monthly precipitation values to transform the data such that the annual averages are normalized. Thus, SPI is the number of standard deviations that the observed value would deviate from the long-term mean for a normally distributed random variable. SPI transforms precipitation data into a standardized score which allows comparisons across regions with vastly different climates, something raw rainfall variability cannot do effectively. SPI can also be calculated over various timescales making it useful for assessing short-term and long-term hydrological droughts (McKee, Doesken, and Kleist 1993). The World Meteorological Organization (WMO) recommends SPI as the standard for monitoring meteorological droughts worldwide (World Meteorological Organization 2020). While Rainfall variability measures fluctuations but it does not indicate whether those fluctuations are abnormal for a specific region or time of year. And unlike SPI, rainfall variability does not offer a normalized scale, making it harder to interpret or compare across locations. Regarding Extreme Precipitation Days, it is more event focused and not trend focused: highlighting isolated heavy rainfall events but not capturing cumulative deficits or surpluses over time.

The climatology literature (McKee, Doesken, and Kleist 1993; Cheval 2015) define various negative and positive SPI levels that characterize rainfall. This study is concerned with positive rainfall shocks or SPI of at least >0.50 . Positive rainfall may be beneficial and particularly in the context of arid and semi-arid lands. However, to a certain degree, excessive rainfall and flooding have a negative impact on health as they create an environment suitable for disease proliferation that is detrimental to young children and reduce agricultural outcomes (Cooper et al. 2019; Omiat and Shively 2020).

3.3.3 Study variables

Health outcomes

Catch-up growth is the health outcome of interest. The definition of catch-up growth requires at least two observations available over time for an individual. In this study, we focus on catch-up growth in weight, as weight is the only size measure available at birth and in the survey year. Following the literature, we define two types of catch-up growth in weight, namely absolute and relative measures (Casale, Desmond, and Richter 2020; Leroy et al. 2015; Anand et al. 2018).

Absolute catch-up growth in weight is defined as a decrease in the absolute deficit in weight, measured in gram, between two points in time for an individual. This means that catch-up growth occurs if the weight for Age Difference (WAD) deficit in gram declines. The WAD is calculated as the difference between the measured weight and the median sex and age-specific weight obtained from the WHO growth standards. The WAD variable is not included in the Kenya DHS. Thus, we computed the two WAD indicators at birth and during the survey year for all children with a recorded birth weight.

Relative catch-up, on the other hand, is mostly used in the literature based on the variability in the Weight for Age z (WAZ) score. This can be defined as an improvement in WAZ over time. The WAZ scores in the year of survey are provided in the DHS dataset. We calculated the the WAZ score at birth using the WHO Infant Weight for Age Z scores calculations⁹ to convert the birth weight into z scores. Following Desmond and Casale (2017), we include alternative measures of catch-up growth in other sections of the chapter.

Rainfall measures

In line with the climatology literature (McKee, Doesken, and Kleist 1993), we define positive rainfall shocks in a district and year to be 1 for values of the SPI more or equal to 1

⁹<https://www.msmanuals.com/professional/multimedia/clinical-calculator/who-infant-weight-for-age-percentiles-24-months>

and 0 otherwise – with the following thresholds: Mild Moisture is an SPI more or equal 0.50; Moderate moisture, an SPI ranging from 1- 1.49; Exceptional moisture SPI from 1.50 - 1.99 and Extreme Moisture for SPI of more than 2. Following (Dinkelman 2017; Hyland and Russ 2019), we define four major indicators to capture exposure to positive rainfall shocks. These are cumulative measures capturing positive rainfall shocks exposure in a child’s earliest life. They represent the proportion of years from the calendar year of birth (t) to the second/fourth calendar year after birth (t+2)/(t+4), when SPI is more or equal to 0.50 in the district of residence. Measuring rainfall shock as a percentage of years spent in positive moisture allows us to capture multiple events across many years, rather than relying on a single shock event. Studies that rely on a single event face a number of empirical difficulties. For example, the duration of the event might be too brief to produce an impact. Furthermore, the event might impact a relatively small portion of the population, which might render it difficult to obtain reliable effect estimates that would normally benefit from large sample analysis (Shige Song 2014). We define two main indicators, the first one is the moderate moisture with an $SPI \geq 1$ and the second, exceptional moisture with an $SPI \geq 1.5$. However, we also investigate the effect of minor shock or mild moisture ($SPI \geq 0.50$) and extreme shocks ($SPI \geq 2$).

Other variables

Following the literature, we include two sets of variables, mother and child characteristics as well as household composition. The first set includes the mother’s weight and height to capture the child’s genetic potential, the number of children ever born, and age. We also include the child’s age in months, gender, and birth order. The second set contains the household’s socioeconomic status variables, specifically the mother’s years of education and wealth index. The wealth index is a composite measure of a household’s cumulative living standard in DHS. It is calculated based on households’ ownership of selected assets, such as televisions and bicycles, materials used for housing construction, and types of water sources and sanitation facilities. In the literature, anthropometric measurement are

attributed not only to genetic, environmental factors, and nutrition but also to ethnicity (Lee et al. 2014; Lambert et al. 2020; Bhat, Jindal, and Acharya 2021), we, therefore, control for ethnicity and find that it has an impact on child anthropometry, but the magnitude is negligible.

3.4 Methods

3.4.1 Catch-up growth

In order to assess the occurrence of catch-up growth in LBW children, we calculate the percentage of LBW children who experience catch-up growth at one, two, three and four year (s). This allows us to investigate whether children can catch up at ages two years and beyond. In line with Desmond and Casale (2017), we use absolute, relative, and other alternative definitions to identify the incidence of catch-up growth in weight in this study: (i) Positive change in WAZ, WAZ in survey year $>$ WAZ in birth year; (ii) Recovery from LBW, WAZ in survey year $>$ -2); (iii) Positive change in WAD, WAD in survey year $>$ WAD in birth year; (iv) Near normal range, WAZ in survey year $>$ -1; (v) Recovery from LBW and Positive change in WAD.

3.4.2 Impact of positive rainfall shocks on catch-up growth

Furthermore, this study investigates whether favorable early-life rainfall is a remedial investment for LBW children. In order to identify the impact of early-life positive rainfall shock exposure on catch-up growth in weight, we use the variation in favorable rainfall experienced in childhood as the quasi-random experiment. We assume that the occurrence of a positive rainfall shock event is quasi-random within and across districts on a year-to-year variation, which is considered exogenous (Maccini and Yang 2009; S. Kumar, Molitor, and Vollmer 2016; Abiona 2017). We merge birth information with weather data by linking the

year and district of birth with the district-specific rainfall measures. This strategy allows us to compare the catch-up growth between cohorts exposed and not exposed to positive rainfall shock across birth years and districts (Rocha and Soares 2015; Dinkelman 2017).

This relationship is captured by the following equation:

$$Y_{id} = \beta_0 + \beta_1 PosRain_{idt} + \beta_2 X_i + \mu_d + \omega_t + \epsilon_{id}$$

Where Y_{id} represents the outcomes of interest of child i born in district d . The outcome of interest, the catch-up growth, is the positive change in WAZ. We also include another catch-up measure, positive change in WAD. $PosRain_{idt}$ represents a cumulative measure of exposure to positive rainfall shock in a child's earliest life in line with (Dinkelman 2017; Hyland and Russ 2019). It measures the proportion of years from the calendar year of birth (t) to the second ($t+2$) and fourth ($t+4$) calendar years respectively, during which is more than 1 in the district of residence. Measuring favourable rainfall shock as a percentage of years spent in positive rainfall allows us to capture multiple events across many years rather than rely on a single positive rainfall shock. β_1 is the main coefficient of interest that quantifies the effect of exposure to average positive rainfall shock. The estimates of β_1 are considered unbiased since rainfall shock events are exogenous; X represents other variables in the regression; we include two sets of variables, namely mother and child characteristics and household composition. The first set includes the mother's weight and height to capture the child's genetic potential, the number of children ever born and number of children under 5 years and age and child birth order. The second set contains the household's socioeconomic status variables, specifically the mother's years of education and wealth. We also control for ethnicity since the literature points out to an existing correlation between ethnicity and anthropometrics (Lambert et al. 2020). The variable μ_d is a district of birth fixed effects that control for the constant unobservable difference between district that may affect outcomes; ω_t is the birth year fixed effects that account for age effects as well as

contemporaneous national shocks affecting these outcomes. ϵ_{idt} is the idiosyncratic error term that accounts for any correlation of errors within districts. We run a probit model for each child because our outcomes variables are binary.

3.5 Results

We begin by describing the main features of the data, followed by a presentation of the main results and a sensitivity analysis.

3.5.1 Descriptive statistics

This section provides the summary statistics for the variables included in the regression analysis, which examines the potential impact of rainfall on LBW children. To conduct this analysis, we merge district-level rainfall data with district-level information from the DHS. Unlike previous rounds, which presented data at the provincial level, the 2014 DHS offers information categorized by district. Of the 21,937 children included in the 2014 Kenya DHS, 5,911 have recorded birth weights. Among these, 665 children have a birth weight of ≤ 2500 grams for the analysis which exclude cases with missing anthropometric information.

Descriptive information is presented in Table 3.1. On average, our mothers have limited education, only about seven years, but have an average of 3 children ever born, two of which are under the age of 5. In terms of age, mothers are approximately 29 years, while children are slightly more than two years old. In terms of weight, the average WAZ at birth for this sample of LBW children is nearly three standard deviations below the expectation. The World Health Organisation (World Health Organization 2008), uses a z score of two standard deviations below 0 to define underweight, while overweight is based on two standard deviations above the reference population. The distribution of WAZ at birth and during the year of survey are depicted in figure 3.1 for children aged 0 to 59 months. The WAZ at

birth is totally to the left of center (0) while there observations to the right of the center (0) during the year of survey demonstrating that catch-up growth occurs among LBW children in Kenya. Figure 3.2 illustrates a similar pattern for the WAD measure.

On average, individuals spend 19 % of their lives from birth year to age four in a moderate moisture defined as an SPI ≥ 1 and approximately 13 % in exceptional moisture with an SPI ≥ 1.5 from birth to and including age four.

Table 3.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Mother age	662	28.40	6.71	15	48
Mother height in cm	662	158.85	6.67	129.90	196.70
Mother weight in kg	662	59.33	13.94	36.30	166.10
Mother years of education	662	7.71	3.90	0	16
Children ever born	662	3.33	2.23	1	13
Children under 5 Child	662	1.74	0.81	0	6
Child birth order	662	3.06	2.20	1	13
Weight for age z scores at birth	662	-2.54	1.01	-8.77	-1.73
Weight for Age z scores in survey year	662	-1.11	1.11	-5.06	3.57
Weight for Age Difference at birth	662	-0.004	0.06	-1.20	0.00
Weight for Age difference in survey year	662	-1.53	1.60	-8.48	4.58
Fraction of childhood in Mild moisture	662	0.33	0.36	0.00	1.00
Fraction of childhood in Moderate moisture	662	0.19	0.31	0.00	1.00
Fraction of childhood in Exceptionel moisture	662	0.13	0.26	0.00	1.00
Fraction of childhood in Extreme moisture	662	0.05	0.18	0.00	1.00

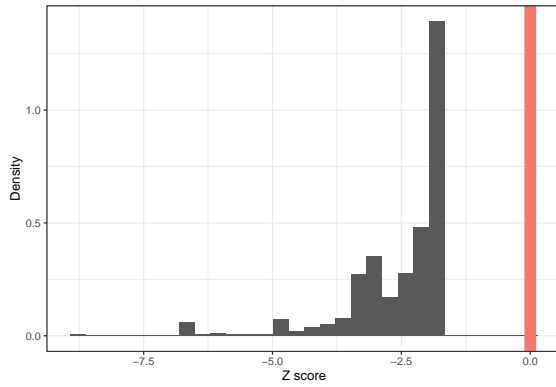
Notes: The summary statistics are based on data from the 2014 Kenya DHS.

3.5.2 Overall estimates

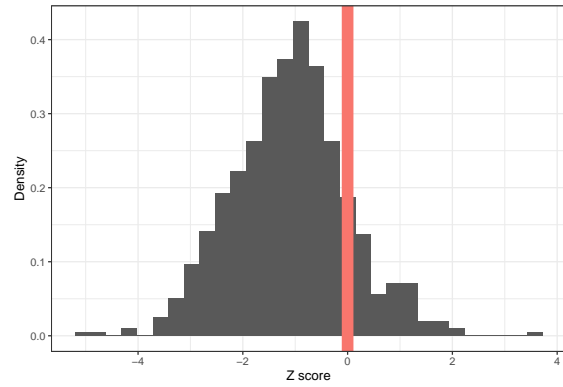
We start by presenting the results of the catch-up growth, dive into the impact of positive rainfall shocks on catch-up growth in weight and finally present the estimates of the other variables included in the regression.

Catch-up growth

Tables 3.2 present the incidence of catch-up growth among LBW children from one year

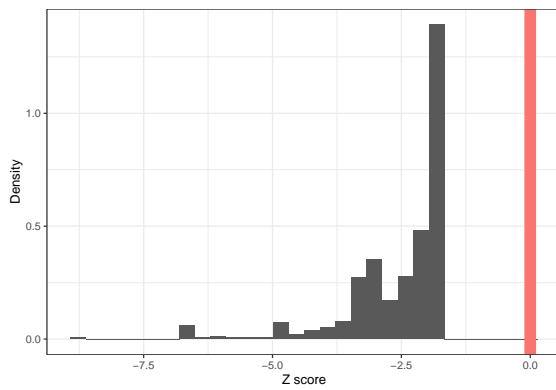


(3.1.1) WAZ B

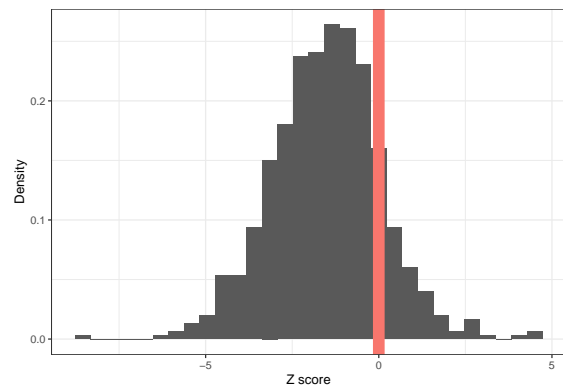


(3.1.2) WAZ S

Figure 3.1: Weight for age z-score (WAZ birth year) and weight for age z-score (WAZ survey year)



(3.2.1) WAD B



(3.2.2) WAD S

Figure 3.2: Weight for age z-score (WAD birth year) and wheight for age z-score (WAD survey year)

to four years using the five rounds of Kenya DHS with LBW defined as birth weight of ≤ 2500 grams and across five definitions of catch-up growth (Desmond and Casale 2017). Overall, catch-up growth can be observed across all definitions despite the variation in the percentages.

In panel 1, we see that 92% of children with LBW experienced a positive change in WAZ at the time they reached one year of age, indicating that their weight deficit was reduced. When we impose an additional criterion requiring LBW children to have crossed the -2 standard deviation (SD) WAZ cut-off by these ages, we find that 75% of children caught up or recovered. Another definition of catch-up growth is to be closer to the normal range, namely a WAZ of ≥ -1 . Under this criterion, 50% of LBW children caught up. Regarding absolute catch-up growth, where children need an absolute decrease in weight deficit in grams, the catch-up rates are much lower, only 19% experience a catch-up growth. When we combine two definitions-requiring that LBW children have crossed the -2 SD WAZ threshold and have reduced their absolute weight deficit- we find that only 19% of children caught up. Panel 2 shows that the incidence of catch-up growth is higher at 2 years of age than at 1 year and similar trends can be observed across the different definitions. In panels 3 and 4, while the percentages of catch-up growth decrease, except for the positive change in WAZ, there is still evidence of catch-up growth occurring beyond the first two years of life.

The results indicate that the extent of catch-up growth varies depending on the definitions used. Generally, catch-up growth in weight, measured as the positive change in WAZ, shows the highest percentage across all age groups. In contrast, the positive change in WAD has the lowest percentage of catch-up growth. Nevertheless, regardless of the definition, catch-up growth occurs at various ages included in the sample. These findings are in line with Desmond and Casale (2017) who reported that catch-up growth as positive change in WAZ leads the highest observed rate of recovery.

Table 3.2: Percentage of LBW children who experienced catch up between 2 and 4 years, using different definitions of catch up

Definitions	Age 1		Age 2		Age 3		Age 4	
	Percentage	N	Percentage	N	Percentage	N	Percentage	N
Positive WAZ	91.63	251	94.22	225	96.17	209	94.05	168
Recovery from LBW	74.50	251	85.33	225	82.78	209	76.79	168
Positive WAD	18.73	251	16.44	225	5.74	209	8.33	168
Near normal	49.80	251	55.56	225	49.28	209	36.90	168
Recovery from LBW and Positive WAD	18.73	251	16.44	225	5.74	209	8.33	168

Note: The sample is from the pooled 5 rounds of Kenya DHS survey. Data is restricted to those children who had birthweight <2500g and valid weight values during the year of survey. Recovery from LBW = WAZ in survey >-2, Near normal = WAZ in survey year >-1 .

Impact of positive rainfall shocks on catch-up growth

We present the results of the impact of positive rainfall shocks on catch-up growth in weight for children with a birth weight ≤ 2500 grams using the 2014 Kenya DHS while specifying four cumulative rainfall shocks measures defined previously, namely, Mild moisture, Moderate moisture, Exceptional moisture and Extreme Moisture. The dependent variable is the catch-up growth in weight, expressed as the positive variation in either WAD (absolute definition) or WAZ (relative definition). In addition of rainfall shocks, our estimations include other variables such as mother and child characteristics: mother's weight and height to capture the child's genetic potential, the number of children under five years in the household and child birth order. Also included are the household's socioeconomic status variables, specifically the mother's years of education and wealth score. Ethnicity is also controlled for due to possible correlation between ethnicity and anthropometrics. We run a probit model since the outcome variables are binary.

Tables 3.3 – 3.6 provide the results of the probit estimation of the impact of cumulative rainfall shocks on a positive change in WAD (absolute catch-up) and a positive change in WAZ (relative catch-up) from birth year up to two and four years respectively. In Tables 3.5 and 3.6, the coefficients of mild and moderate moisture are positive and significant at four years for the change in WAZ while exceptional and extreme moisture coefficients are negative in both tables. For the change in WAD, all three coefficients are positive at age two and four except for extreme moisture which remains negative throughout. The positive coefficients, though not always significant suggest that positive rainfall shocks may generally improve child health. In contrast, the effects of exceptional moisture are mixed with positive and negative coefficients for the WAZ and WAD while extreme moisture is consistently showing negative effects. This may be due to heavy rainfall increasing the occurrence of diarrheal diseases due to changes in the environment (Tiwari, Jacoby, and Skoufias 2017; Cooper et al. 2019). We acknowledge that some of our regression results show variability in the estimated effect of moisture on child growth across different model

specifications. This reflects the sensitivity of the association to the inclusion of certain controls (e.g., socioeconomic factors, maternal health indicators) and sample restrictions. In the discussion section, we have explicitly highlighted that our results are mixed except for the moderate positive rainfall, and we have indicated that may be due to the small sample size as well as the complexity of isolating the causal impact of moisture on growth outcomes. For our future research we will thrive to get a larger sample size of low birth weight children which we believe will generate more consistent results.

Table 3.3: Impact of positive rainfall shocks on catch-up growth (positive change in WAD) up to 2 years

	Positive change in WAD			
	(1)	(2)	(3)	(4)
Mild moisture	0.593* (0.323)			
Moderate moisture		0.733* (0.382)		
Exceptional moisture			0.302 (0.421)	
Extreme Moisture				-0.164 (0.535)
Num.Obs.	662	662	662	662
F	50.537	52.051	52.599	52.773
RMSE	0.31	0.31	0.31	0.31
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAD; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights ≤ 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5.3 Other factors influencing catch-up growth

We further the analysis to investigate other determinants of catch-up growth in weight including the two sets of variables described above, namely mother and child characteristics as well as household specifics. In table 3.7, we show that mother's weight and height are positively associated with catch-up growth. Studies have demonstrated the association between parental factors through genetics, epigenetics, intrauterine and postnatal environment, and their offspring growth (Griffiths, Dezateux, and Cole 2007; Varela-Silva et al. 2009; Miele et al. 2022; Strain et al. 2022; Øyri et al. 2023). However, the mother's height and weight coefficients are not significant and their magnitude remains small. Birth order is significant and negative for catch-up define as WAZ while it is positive and insignificant

Table 3.4: Impact of positive rainfall shocks on catch-up growth (positive change in WAD) up to 4 years

	Positive change in WAD			
	(1)	(2)	(3)	(4)
Mild moisture	0.555 (0.338)			
Moderate moisture		0.716* (0.404)		
Exceptional moisture			0.299 (0.442)	
Extreme Moisture				-0.209 (0.553)
Num.Obs.	662	662	662	662
F	50.660	52.114	52.632	52.798
RMSE	0.31	0.31	0.31	0.31
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAD; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights ≤ 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

for WAD. SES factors are known to influence child development, with children living in the poorest households being the most disadvantaged. Our findings are similar to Behrman et al. (2024) and Outes and Porter (2013) who find that children in better-off households experience a higher catch-up rate than those in poor households. Of the SES variables, mother's education is positively associated with the probability of catch-up in the case of positive WAZ but it remains not significant. Another significant variable in socioeconomic status (SES) is the wealth index. The wealth coefficients are positive and statistically significant for both the positive change in WAZ and the positive change in WAD. This indicates that belonging to a wealthier family increases the likelihood of recovering from below-average birth weight.

Table 3.5: Impact of positive rainfall shocks on catch-up growth (positive change in WAZ up to 2 years)

	Positive change in WAZ			
	(1)	(2)	(3)	(4)
Mild moisture	-0.109 (0.375)			
Moderate moisture		0.257 (0.393)		
Exceptional moisture			0.022 (0.452)	
Extreme Moisture				0.008 (0.523)
Num.Obs.	662	662	662	662
F	61.228	61.298	61.553	61.317
RMSE	0.31	0.31	0.31	0.31
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAZ; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights ≤ 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Impact of positive rainfall shocks on catch-up growth (positive change in WAZ) up to 4 years

	Positive change in WAZ			
	(1)	(2)	(3)	(4)
Mild moisture	-0.119 (0.392)			
Moderate moisture		0.215 (0.423)		
Exceptional moisture			0.049 (0.478)	
Extreme Moisture				-0.023 (0.540)
Num.Obs.	662	662	662	662
F	61.277	61.292	61.569	61.394
RMSE	0.31	0.31	0.31	0.31
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAZ; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights ≤ 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7: Multivariate probit regression analysis of incidence of catch up between the year of birth and two years

	Positive change in WAZ		Positive change in WAD	
	(1)	(2)	(3)	(4)
Birth order	-0.014 (0.035)	-0.013 (0.035)	-0.020 (0.042)	-0.021 (0.042)
Children under 5	-0.226 * * (0.094)	-0.229 * * (0.094)	-0.247 * * (0.112)	-0.242 * * (0.113)
Mother Height	0.017 (0.013)	0.016 (0.013)	0.026 * * (0.013)	0.025* (0.013)
Mother weight	0.018 * * (0.008)	0.018 * * (0.008)	0.030 * * * (0.006)	0.030 * * * (0.006)
Mother Education	0.002 (0.026)	0.003 (0.026)	0.061* (0.034)	0.060* (0.035)
Ethnicity	0.006 (0.004)	0.006 (0.004)	0.002 (0.005)	0.002 (0.005)
Wealths	0.070 (0.112)	0.064 (0.111)	0.024 (0.110)	0.026 (0.110)
Mild moisture	-0.109 (0.375)			
Moderate moisture		0.257 (0.393)		
Exceptional moisture			0.302 (0.421)	
Extreme Moisture				-0.164 (0.535)
Num.Obs.	662	662	662	662
F	61.228	61.298	52.599	52.773
RMSE	0.31	0.31	0.31	0.31
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAZ and WAD; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights ≤ 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6 Sentivity analysis

We conduct some sensitivity analysis with alternative specifications of catch-up growth in weight and a different definition of LBW to test the validity of the results described in the previous sections.

First, we estimate catch-up growth by regressing WAZ scores in the second period (Survey year), on the WAZ at birth (first period) as in Hoddinott and Kinsey (2001) and Outes and Porter (2013). The coefficient of the lagged WAZ represents the catch-up growth. The results in Tables 3.8 and 3.9 show that WAZ at birth is positive and significant suggesting the occurrence of catch-up growth in weight. Looking at the variables that contributed to this catch-up growth, most of the rainfall variables are positive although not significant; birth order, number of children under 5 and ethnicity significantly lower child health while wealth, mother's height and weight increase the chances of catch-up growth.

In another sensitivity exercise, we use the definition of LBW as birth weight $<2500\text{g}$ although we have only few observation. We analyse the role of positive rainfall shocks on catch-up growth as positive change in WAZ or WAD and the results are shown in Tables C.1 and C.2. We find that, at ages two and four, maternal weight and household wealth significantly contribute to catch-up growth. Mild moisture show a positive but statistically insignificant effect.

Table 3.8: Impact of positive rainfall shock on WAZ at two years

	(1)	(2)	(3)	(4)
WAZ at birth	0.176 *** (0.043)	0.179 *** (0.044)	0.176 *** (0.044)	0.178 *** (0.043)
Birth order	-0.027 (0.020)	-0.026 (0.020)	-0.027 (0.020)	-0.026 (0.020)
Children under 5	-0.183 *** (0.063)	-0.184 *** (0.064)	-0.181 *** (0.063)	-0.182 *** (0.064)
Mother Height	0.014 ** (0.007)	0.014 ** (0.007)	0.014 ** (0.007)	0.014 ** (0.007)
Mother weight	0.015 *** (0.003)	0.015 *** (0.003)	0.015 *** (0.003)	0.015 *** (0.003)
Mother Education	0.021 (0.014)	0.020 (0.014)	0.019 (0.014)	0.020 (0.014)
Ethnicity	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Wealths	0.131 ** (0.060)	0.129 ** (0.060)	0.135 ** (0.060)	0.134 ** (0.060)
Moderate moisture		0.181 (0.209)		
Exceptional moisture			-0.194 (0.268)	
Num.Obs.	662	662	662	662
R2	0.277	0.276	0.276	0.276
F	4.215	4.253	4.175	4.205
RMSE	0.94	0.94	0.94	0.94
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAZ and WAD; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights less or equal to 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9: Impact of positive rainfall shock on WAZ at four years

	At age two		At age four	
	(1)	(2)	(3)	(4)
WAZ at birth	0.176 * ** (0.043)	0.179 * ** (0.043)	0.176 * ** (0.044)	0.178 * ** (0.043)
Birth order	-0.027 (0.020)	-0.026 (0.020)	-0.027 (0.020)	-0.026 (0.020)
Children under 5	-0.183 * ** (0.063)	-0.184 * ** (0.064)	-0.181 * ** (0.063)	-0.182 * ** (0.064)
Mother Height	0.014 * * (0.007)	0.014 * * (0.007)	0.014 * * (0.007)	0.014 * * (0.007)
Mother weight	0.015 * ** (0.003)	0.015 * ** (0.003)	0.015 * ** (0.003)	0.016 * ** (0.003)
Mother Education	0.021 (0.014)	0.020 (0.014)	0.019 (0.014)	0.020 (0.014)
Etnicity	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Wealths	0.131 * * (0.060)	0.129 * * (0.060)	0.135 * * (0.060)	0.134 * * (0.060)
Moderate moisture		0.187 (0.229)		
Exceptional moisture			-0.189 (0.282)	
Num.Obs.	662	662	662	662
R2	0.277	0.276	0.276	0.276
F	4.212	4.250	4.185	4.210
RMSE	0.94	0.94	0.94	0.94
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as lagged WAZ; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weights less or equal to 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.7 Discussion

This study investigates the role of positive rainfall shocks as a remediation intervention for LBW children in an arid climate. Children born with a low birth weight present a higher risk of incurring adverse short and long-term outcomes compared to children born with normal weight (Fernandes et al. 2019; Vizzari et al. 2023). The study is relevant for a country like Kenya which consists of approximately 80 percent Arid and Semi-Arid Lands (ASALs) with irregular rainfall and where the livelihoods of the population are closely connected to weather patterns. In this context, positive rainfall shocks might be beneficial for LBW children and improve their chances of catching up on their growth trajectory.

The study begins by analyzing catch-up growth at ages one, two, three and four years to determine whether catch-up continues after the first two years of life. The results indicate that catch-up growth for LBW children occurs at all four years for the five definitions of catch-up growth analysed: (i) Positive change in WAZ, WAZ in survey year >WAZ in birth year; (ii) Recovery from LBW, WAZ in survey year >-2); (iii) Positive change in WAD, WAD in survey year >WAD in birth year; (iv) Near normal range, WAZ in survey year >-1; (v) Recovery from LBW and Positive change in WAD. These findings align with Desmond and Casale (2017), who find that children stunted at two years old experienced catch-up growth at age five.

We then analyse the role of positive rainfall shocks as an intervention strategy that increases the chances of catch-up growth. Studies have investigated the role of biological, Socio Economic Status, and environmental factors in influencing catch-up growth but have not directly explored the impact of rainfall shocks. Following the catch-up literature, we consider the absolute and relative definitions of catch-up growth through the WAD and WAZ. We find that exposure to moderate cumulative positive rainfall shocks benefits children in general. These findings align with the literature, which states that when the constraint is removed, stunted children can experience catch-up growth (Frongillo, Leroy, and Lapping

2019).

There are several pathways through which positive rainfall may impact child growth and health. In the context of developing economies, particularly in Africa, the first channel through which early-life rainfall can impact health is agricultural outcomes and nutrient intake. Agriculture employs over 60% of the workforce, and 96% of cropland is rainfed. Therefore, favourable rainfall in rural settings improves households income and food security through better crop and livestock (Maccini and Yang 2009; Adhvaryu et al. 2023).

In Kenya, over 70% of the population lives in rural areas. Agriculture plays a central role in the country's economy, with the sector accounting for 65% percent of the export earnings and providing livelihood in terms of employment, income, and food security for more than 80 percent of Kenyans (FAO, 2024) ¹⁰. Even though more than 95% agricultural production in Kenya relies on rain-fed farming, only 17% of the country's arable land is actually suitable for this type of agriculture. The 83% that remain requires irrigation to support optimal crop growth owing to insufficient precipitations. However, despite this need, irrigated fields account for only about 2% of the total cultivated land in Kenya (Hornum and Bolwig 2020). Pastoral and agro-pastoral livelihoods dominate in Kenya's hot, arid, semi-arid ASALs, where the population relies on a mixture of livestock and crop production. Thus, positive rainfall is beneficial to households.

Water availability is another pathway through which positive rainfall may contribute to catch-up growth in weight. Arid and semi-arid regions face water scarcity, which entails regular water collection for consumption, hygiene, and other household needs. Lack of adequate access to water has been linked to an increase of the incidence of waterborne and infectious diseases such as diarrhea, which result in poor food absorption and increased malnutrition (Rhue et al. 2023). These effects are further compounded by droughts that have become more frequent due to climate change. In this context, a positive rainfall shock is an event that might benefit child growth. The availability of sufficient water could reduce

¹⁰<https://www.fao.org/kenya/fao-in-kenya/kenya-at-a-glance/en/>

the time spent fetching water and facilitate household choices for adopting healthy WASH behaviors, such as washing hands with water and soap, thus reducing the risk of infectious diseases that have adverse consequences on the nutritional status of children (Shrestha, Vicendese, and Erbas 2020).

We also investigate the impact of other variables on catch-up growth in weight. Wealth positively correlates with catch-up growth, for instance Outes and Porter (2013) and Behrman et al. (2024) observe that the better-off household in quintile 5 having the highest coefficient of catch-up growth. Studies have demonstrated linkages between socioeconomic inequalities and health disparities; the most vulnerable socioeconomic categories are more likely to suffer from negative health outcomes (Sorci 2024). However, although the coefficient is positive, we do not find a significant association between catch-up in weight and the mother's years of education. Our results also highlight that maternal weight, and height positively impact LBW children's growth which is consistent with the findings of Casale, Desmond, and Richter (2020). However, the magnitude of these coefficients are small in our study.

There some limitations to this study. First, we do not have access to longitudinal data. Some researchers argue that catch-up growth measured using cross-sectional datasets does not capture well the changes that have occurred in the environment and other factors (Adair 1999; Hirvonen 2014). Second, our analysis of catch-up growth for LBW children was constrained by the limited sample size. According to the World Health Organization (WHO), LBW is defined as a birth weight below 2,500 grams (approximately -2 standard deviations (SD) from the mean). However, in the 2014 Kenya Demographic and Health Survey (DHS) dataset, only about 28% of children had recorded birth weights, resulting in a small sample of LBW children. To address this, we pooled data from five rounds of the Kenya DHS to examine catch-up growth up to age two and beyond. For the analysis of impact of positive rainfall shocks, we merged sub-administrative rainfall data with the 2014 DHS round that contains district-level information and increase the sample size of LBW by expanding the

LBW definition to ≤ 2500 grams and also reported the findings related to LBW of < 2500 grams.

3.8 Conclusion

We investigate the role/effect that an intervention during early childhood plays in mitigating the adverse impact of LWB. We explore whether positive rainfall increases the likelihood of catch-up growth in weight for LBW children in developing countries where interventions to remediate adverse early life conditions are scarce. We leverage the fact that in Arid and semi-arid lands (ASALs), positive rainfall is a beneficial event, and also, in an agrarian setting with rain-fed agriculture such as Kenya, weather plays a crucial in determining households income and nutrient intake, which in turn have implications for children's health.

We merge data from the 2014 Kenya Demographic and Health Surveys and climate data from the Climate Research Unit's Time-Series. We compute the Standardised Precipitation Index (SPI) for each district per year using the monthly precipitation series from 1950-2014, to construct cumulative positive rainfall shocks exposure namely, Moderate moisture and Exceptional moisture. We then investigate the impact of positive rainfall fluctuations on weight among children aged 0 - 59 months in Kenya. Our results show that cumulative exposure to moderate positive rainfall shocks may increase the likelihood of catch-up growth in weight for LBW children.

Second, this study attempts to overcome the endogeneity linked to the determinants of catch-up growth in the literature. Because catch-up growth is determined by comparing two distinct periods, the relationship between two nutritional periods might suffer from endogeneity concerns as resulting outcomes and investments are determined by the preferences of parents and access to resources by families (Adhvaryu et al. 2023). Furthermore, unobserved parental investments and genetic potential could lead to biased and inconsis-

tent estimates of catch up growth (Outes and Porter 2013). Thus, we exploit the exposure to rainfall as a quasi-random and exogenous event to achieve plausibly better estimates of catch up growth for LBW children.

The study also examines the impact of other variables on catch-up growth in weight namely mother and child characteristics as well as household specifics. We show that maternal weight and height are positively associated with catch-up growth; however, the associations are not statistically significant, and their magnitudes remain small. Birth order is significant and negatively impacts health. Mother's education is positively associated with the likelihood of catch-up growth, as measured by a positive change in WAZ. Another significant variable is the household wealth index.

Climate change is predicted to exacerbate water scarcity even further through declines in precipitation and increases in evapotranspiration rates. To increase the likelihood of catch-up growth for LBW children in regions that are experiencing declining rainfall, several strategies should be implemented to improve nutrition, access to water, and overall living conditions. These strategies include among others, enhancing agricultural resilience, investing in water and sanitation infrastructure, and promoting social protection programs.

4 CHAPTER 4 Environmental and socioeconomic factors: Covid-19 cases in Cape Town

4.1 Introduction

The coronavirus 2019 (Covid-19) pandemic led to increased need for medical services overwhelming health systems that were not prepared to manage the surge (Adabavazeh, Nikbakht, and Tirkolaei 2023; Paschoalotto et al. 2023; Ardakani et al. 2023). Poor health strained health care systems, while government regulations further dampened economic activity around the world (Nicola et al. 2020; Ardakani et al. 2023). Developing countries were among the most affected (Nicola et al. 2020; Ozili 2021; Naseer et al. 2023; Angelov and Waldenström 2023). South Africa identified its first case of Covid-19 on 5 March 2020. Within 18 days, 402 cases were reported. Thus, the country was facing rapid community transmission (Pillay et al. 2021).

The South African government swiftly implemented various measures to control, prevent, contain and reduce the transmission of the virus by introducing non-pharmaceutical interventions including lock-downs, maintaining of physical distance, use of masks, sanitizing using alcohol-based solutions and quarantines (Modisenyane et al. 2022). South Africa implemented some of the strictest lock-downs in the world (Stiegler and Bouchard 2020; Greyling, Rossouw, and Adhikari 2021).¹¹ Initially, economic activities were restricted, apart from essential services, including: healthcare, security, agriculture, and the transport of selected goods (Asmal and Rooney 2021). These controls significantly impacted the economy and population. GDP shrank by 7.0 percent in 2020, compared to 2019, marking the largest decline in economic activity since 1946.¹² Approximately 2.2 million people

¹¹The first lock-down was effective from 26 March 2020 to 30 April 2020, with the strictest measures, including: travel bans and schools closures, among other things. Thereafter, various levels of lock-down ranging from 5 to 1 placed a series of restrictions on activities, movements and gatherings (South African Government 2020).

¹²<https://www.statssa.gov.za/?p=14074>; Department of Statistics South Africa. Accessed on 20 June 2024.

lost their jobs in the second quarter of 2020, erasing ten years of job growth (Köhler et al. 2021). Women were disproportionately affected: 22.5% employment reduction, compared to 9.8% for men, between February and April 2020 (Casale and Shepherd 2022).

The impact of lock-downs could have different effects for the rich and the poor. At the individual level, lock-down likely exacerbated threats to mental health, in a country in which one in three individuals develop a psychiatric disorder at some point in their life (Naidu 2020). It also likely increased violence against women and children (Mahlangu et al. 2022). While all South Africans were affected by the pandemic in various ways, the most vulnerable have been disproportionately impacted, due to structural inequality and poverty, which characterises the South African economy (Nguse and Wassenaar 2021) and landscape. However, the extent to which lock-down measures helped reduce Covid-19 transmission is not well documented, but could offer a better understanding of some of the trade-offs between the economy and the well-being of the population (Shen, Cai, and Li 2020; Qiu, Chen, and Shi 2020). Thus, in this research, we attempt to document it.

There is evidence that human viral outbreaks follow seasonal cycles. Influenza and Human Coronavirus (HCov) display seasonal trends in temperate regions and are characterised by high transmission during winter months. Such cycles are associated with meteorological factors, human activity patterns, immunity and human-to-human contact, amongst others. For instance, extreme cold or heat can result in more time spent in closed and poorly ventilated spaces, which could increase the transmission of Covid-19 (Tang et al. 2020; Nottmeyer et al. 2023). Cold temperatures also increases the stability of the viral load, while low humidity enhances droplet nuclei formation, which can prolong the viability and transmission of the virus (Rosti et al. 2020; Aboubakr, Sharafeldin, and Goyal 2021; Nottmeyer et al. 2023). The literature, including recent reviews (Mecenas et al. 2020; Mcclymont and Hu 2021; Dong et al. 2021; Weaver et al. 2022) and global studies (Nottmeyer et al. 2023; Liu et al. 2022; S. Yuan, Jiang, and Li 2020; J. Yuan et al. 2021b), has investigated the relationship between temperature and relative humidity, arguing these are the most influential

meteorological factors. However, these studies are inconclusive with some finding positive and others finding negative associations between these factors and cases/transmission.

Early studies of the pandemic were limited by the depth of data, and, thus, were often limited to statistical correlations (G. Kumar and Kumar 2020; Tosepu et al. 2020; Menebo 2020). Some studies were not concerned with non-linear relations or potential lagged effects of meteorological factors (Sajadi et al. 2020; Smith et al. 2021). Others were not concerned with possible confounders, such as non-pharmaceutical interventions (NPI) – government lock-down measures – seasonal or other timing issues (S. Gupta, Raghuwanshi, and Chanda 2020; Rosario et al. 2020). Recent studies have attempted to fill these gaps, applying more robust statistical models and accounting for numerous confounders (J. Yuan et al. 2021a; Fong and Smith 2022; Wang et al. 2023; Nottmeyer et al. 2023). However, establishing a clear connection between social determinants of health (SDH) (Organisation 2013) and socioeconomic factors that might influence the spread of the virus have received little attention. Therefore, one contribution we make to the literature is to examine the underlying weather/cases relationship across regions with varying levels of socioeconomic status. We also control for daily case differentials arising from practical realities, NPI, potential lags and complex interactions.

For the most part, the dominant regional focus in the literature has been on the northern hemisphere, such that studies in developing countries are scarce (Wang et al. 2023). Most of the existing studies from Africa (Meo et al. 2020; Ogaugwu et al. 2020; Adekunle et al. 2020) use correlation analysis. Those that do go further, such as Adekunle et al. (2020), which adopts a General Additive Model (GAM), did not include NPI measures and was limited to just 31 observations. Ai, Nie, and Wang (2022) includes 8 countries, including South Africa. Although they apply Distributed Lag Non-Linear Models (DLNM), as do we, their analysis covers large areas and, therefore, may mask more complicated features (Dong et al. 2021). Our focus is more narrow - the city of Cape Town, South Africa. Although our results may not be nationally or even globally representative, averages across the country

or the world are likely to mask important local features and/or heterogeneities that can only be uncovered through regional analysis.

The results indicate non-linearity across temperature and relative humidity, as well as complex relationships over time. There is evidence of increased risk during times of low humidity, although, on average, temperature's importance arises mostly through the lag structure included in the analysis. At high temperatures in low SES areas, lagged temperature is protective against the virus. Also in low SES regions and low levels of humidity, lags are associated with worsening case risk. In middle to high SES regions of the city, both at low and high temperatures, short lags worsen case risk, but longer lags are associated with reduced risk. For humidity, whether for high or low values, increased lags are associated with increased risk of a covid case being reported.

4.2 Data

4.2.1 Background

Cape Town is the capital city of the Western Cape province in South Africa. The city is classified as a Csb Köppen-Geiger climatic zone, i.e. it has a Mediterranean climate with dry and warm summers from (January-April, September-December) and wet and cold winters months from May to August (Peel, Finlayson, and McMahon 2007). Cape Town is the second most populous in the country. According to the 2022 South African Census, the population of the City of Cape Town is approximately 4.77 million, having grown from about 3.74 million in 2011 (Moultrie and Dorrington 2024). All eight health sub-districts were included in the study: Eastern, Khayelitsha, Klipfontein, Mitchells Plain, Northern, Southern, Tygerberg and Western; see Figure 4.1.

South Africa is one of the most unequal countries, reporting a per-capita expenditure Gini 0,65 in 2015 and 0.63 in 2022(City of Cape Town 2022). Extensive inequality is perpetuated

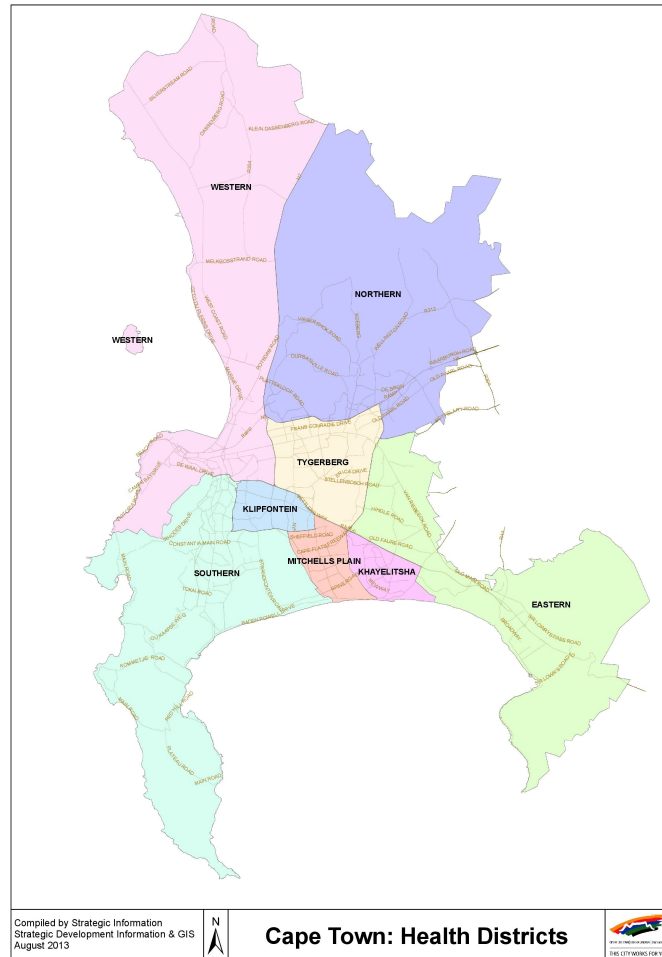


Figure 4.1: City of Cape Town

by a legacy of exclusion and the nature of economic growth, which is not pro-poor and does not generate sufficient jobs (The World Bank 2018). Inequality in the municipal regions are rather similar to the country as a whole. In 2018, Cape Town, eThekweni (Durban), Johannesburg and Tshwane (Pretoria) report Gini coefficients of 0.62, while the Gini in Nelson Mandela Bay (Port Elizabeth) was 0.63 (Affairs and Traditional 2020).

Cape Town is an urban hub, where social and spatial segregation is common. Access to public infrastructure and services also reflect these inequalities. The population is clustered in sub-districts and areas that often correspond to their socioeconomic and cultural differences. To differentiate between the better off (wealthy) and worse off (poor) sub-districts, we refer to the information presented in Table 4.1. These are demographic, socioeconomic and environmental factors, and they are summarised across all eight health sub-districts in the city. Population and area determine the density; we assume crowding is associated with poverty. Employment is the rate of employment, while income less than R3200 (per month) is the share of households with earnings less than that figure. We assume high employment rates are inversely related to poverty, while higher shares of those earning less than R3200 per month is also associated with poverty. Finally, we note the type of housing, which includes formal housing as well as “access” to electricity for heating. We assume that formal housing and access are inversely related to poverty. By those criteria, Khayelitsha, which is located next to the airport and industrial area, is the most crowded sub-district with 101 inhabitants/ha, has the lowest rate of employment, 62%, but highest share of low earnings households. Combining that with formal housing and access to electricity. This sub-district is the poorest.

Table 4.1: Socio-economic factors in Cape Town Health Districts

Indicators	Khayelitsha	Klipfontein	Tygerberg	Western	Northern	Eastern	Southern	Mitchells
Population*	442 721	410 338	730 061	631 290	467 718	704 376	596 859	615 422
Area	4 370 ha	4 275 ha	11 985 ha	66 350 ha	63 180 ha	42 965 ha	48 660 ha	5 000ha
Density	101	96	61	10	7	16	12	38
Employment (aged 15 to 64)	0.62	0.68	0.75	0.82	0.88	0.78	0.84	0.68
Income less than R3200	0.74	0.59	0.45	0.37	0.3	0.46	0.34	0.61
Formal Housing	0.45	0.76	0.89	0.85	0.9	0.82	0.87	0.68
Electricity for lighting	0.81	0.98	0.97	0.94	0.96	0.96	0.98	0.92
Access to piped water	0.62	0.83	0.96	0.9	0.96	0.93	0.93	0.81
Refuse removed once a week	0.81	0.95	0.98	0.98	0.97	0.96	0.96	0.91
Access to a flush toilet	0.72	0.83	0.93	0.9	0.95	0.92	0.92	0.84

Note: Table compiled from the 2013 Cape Town Health District Profiles put together by the Policy and Strategy Department, City of Cape Town, using 2011 Census data supplied by Statistics South Africa. Population data is obtained from the Western Cape Government, CIRCULAR H 102-2020. Mitchells refers to Mitchells Plain.

In addition to Khayelitsha, Klipfontein and Mitchells Plain sub-districts were classified as lower socio-economic status areas, whilst the rest were classified as middle/higher socio-economic status areas: Eastern, Northern, Tygerberg, Southern and Western. Adherence to non-pharmaceutical interventions, such as social distancing and handwashing, may differ between socio-economic status areas (Gibson and Rush 2020). The age structure, general health status, building characteristics and exposure to other environmental risk factors are also expected to differ between the lower and middle/higher socio-economic status areas. Thus, they could affect the association between meteorological factors and Covid-19 incidence.

4.2.2 Data

Covid-19 case data were obtained for all eight sub-districts in the city. The data were recorded by the Western Cape province Covid-19 dashboard, which is publicly accessible online.¹³ Cases were confirmed with the polymerase chain reaction Covid-19 test. Data on personal characteristics such as age, sex, co-morbidities or smoking status are not publicly available. The study period covered 1 March 2020 to 24 January 2021.

Meteorological data, namely Daily minimum and maximum temperature and Daily average relative humidity (%) were obtained from the South African Weather Service (SAWS). Data were from the seven monitoring sites in the Cape Town municipality: Atlantis, Astronomical Observatory, Cape Point, Kirstenbosch, Jonkershoek, Slangkop and Strand.¹⁴

¹³<https://coronavirus.westerncape.gov.za/Covid-19-dashboard>, last accessed in mid 2021

¹⁴Data cleaning and preparation was done with Excel. For the analysis, we use R version 4.4.2 (R Core Team 2023) with the following packages: `haven` (Wickham 2023) to import foreign statistical formats (mainly Stata) into R; `tidyverse` (Wickham 2023) to import, clean, manipulation, transform and present the data; `Splines` for working with regression splines using the B-spline basis and the natural cubic spline basis; `dlnm` to specify and interpret distributed lag linear (DLMs) and non-linear (DLNMs) models; `stargazer` (Hlavac 2022) for summary statistics table, `knitr` (Xie 2024) for dynamic report generation in R; `modelsummary` (Arel-Bundock 2022) for results tables; `kableExtra` (Travison et al. 2024) to construct complex tables and customize them, as needed; `stats` (Hothorn and Zeileis. 2022) to estimate probit models. We further use `rmarkdown` (Allaire et al. 2024) to combine R codes, results from the data analysis and the text into one reproducible document. All code and data are available from the authors, upon request.

4.3 Methods

Daily average temperature and humidity were calculated for each monitoring site from the SAWS data. From this, an overall city daily average was calculated for both. The associations were investigated with generalised linear models, assuming a quasi-Poisson distribution, which is generally used for count data (Islam, Abul, and Azad 2021; Runkle et al. 2020; Fu et al. 2021). Temperature and relative humidity were included as distributed-lag nonlinear model (DLNM) components (Runkle et al. 2020; Zhu et al. 2021; Islam, Abul, and Azad 2021; Fu et al. 2021; Wang et al. 2023; Fong and Smith 2022). Environmental factors often show health effects that are delayed in time. DLNM offers a framework that describes the additional time (lag) dimension of the exposure-response association as it captures both the nonlinear exposure-response and the delayed effects. DLNMs use a cross-basis function to assist in the estimation of the cumulative effects of the environmental exposure over the lags (Gasparrini and Armstrong 2011; Gasparrini 2014).¹⁵

The associations between daily Covid-19 cases, temperature and/or relative humidity were based on the following equation:

$$Y_{jt} = \alpha + BX + \sum_{\ell} \lambda_{\ell} L_{\ell jt} + \sum_d \delta_d d_{jt} + \varepsilon_{jt} \quad (5)$$

where Y_{jt} is the number of recorded Covid-19 cases on day t at location j , which could be the entire city or be separated according to low/high SES. X is the crossbasis matrix of meteorological factors and assumed lag length, such that B is a vector representing the coefficients for all columns of the matrix; see below for additional discussion. L represents the measure of lock-down included in the model – either a one week lead, lag, or its exact timing – while ℓ represents the level.¹⁶ We allow for day of the week fixed effects, denoted

¹⁵We apply natural cubic basis splines, while the splines are limited to three knots, as well as an assumed time lag. Thus, the initial case data is lagged d days, and a spline function is built from that data. We show below that 21 days is a plausible lag length.

¹⁶Here, lead implies moving the entire lockdown period one week earlier; thus, lag moves it one week later. Lock-down level 5 was implemented between 27 March to 30 April 2020, followed by level 4 (1-31

by d with coefficients δ_d , while ε is the error.

A maximum lag of 21 days was investigated to explore the delayed association between Covid-19 cases, temperature and relative humidity. The lag of 21 days was selected, based on the Akaike Information Criterion, but also captures possible delays from exposure to infection and/or seeking a test. Shorter lags of up to 7 and 14 days were also investigated in sensitivity analyses (Runkle et al. 2020; Zhu et al. 2021; Fu et al. 2021). The incubation period between exposure to the SARS-CoV-2 virus and symptom onset has been shown to range from 2 to 14 days (Linton et al. 2020; Lauer et al. 2020).

The cross-basis functions for both temperature and relative humidity were based on a natural cubic spline with three equally spaced internal knots. The internal knots for temperature were at 13.5°C, 18°C and 22.5°C; there were also two boundary knots at the minimum and maximum (9°C, 27°C). The internal knots for relative humidity were 52.8%, 67.5% and 82.3%, with two boundary knots at the minimum and maximum (38%, 97%). The effects of cold and heat are reported as cumulative relative risks (RR) of the 7-day, 14-day and 21-day lag periods, due to the fact that one week intervals are easily interpreted. For analysis purposes, we use the 10th and 90th percentiles of the data; thus, cold corresponded 13°C, while hot was set to 21°C; the median (16°C) was set for the reference (Fu et al. 2021). For relative humidity, dry and humid was set to corresponded to 62% and 94% relative humidity, respectively, whilst the median (reference) was 82%. The choice of reference does not affect the fit of the model. Similarly, different values may be chosen depending on interpretation plans (Gasparrini and Armstrong 2011).

May 2020), level 3 (1 June to 17 August 2020), level 2 (18 August to 20 September 2020) and level 1 (21 September to 28 December 2020). The country was on an adjusted level 3 lockdown level from 29 December 2020 up to the end of the study period (24 January 2021). Fewer tests are conducted over weekends, hence the need to control for day of the week.

4.4 Results and discussion

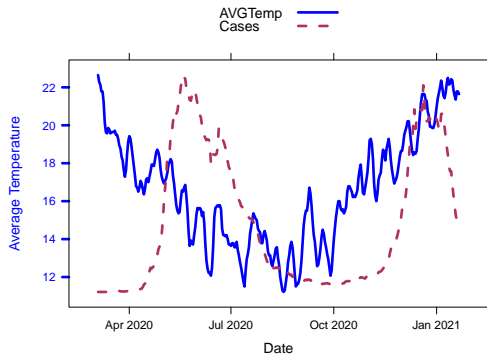
4.4.1 Descriptive statistics

Table 4.2 summarises the number of daily Covid-19 cases, temperatures and relative humidity levels in the city of Cape Town. Recorded daily cases varied between 0 and 3070 during the study period. The lower socio-economic status (LSES) areas (Klipfontein and Khayelitsha sub-districts) recorded the fewest cases in the city, compared to the sub-districts in the middle/higher socio-economic status (MHSES) areas. Daily temperature ranged from 9°C to 27°C, while daily relative humidity ranged from 38% to 97%. Figures 4.2 and 4.3 illustrate the time-series of daily Covid-19 cases, temperatures and relative humidity levels, while distinguishing between LSES and MHSES sub-districts. The peak of the second Covid-19 wave was slightly lower than that of the first wave in the LSES areas, while the second peak in MHSES areas was far higher.

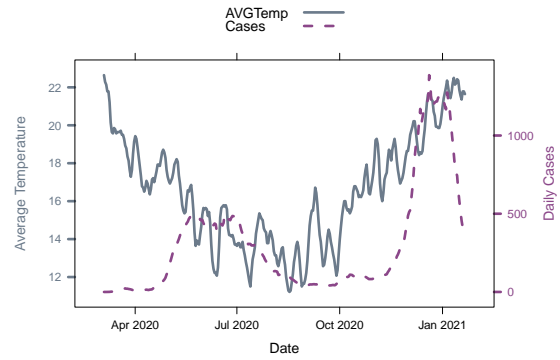
Table 4.2: Summary statistics for the city of Cape Town from March 1, 2020 to January 24, 2021 (330 days)

Statistic	Mean	St. Dev.	Min	Max
City of Cape Town Daily Case Count	510.633	636.635	0	3,070
Avg Temp (c)	16.658	3.427	8.500	26.500
Avg Rel Humidity (%)	79.597	12.239	38	97
Khayelitsha Daily Case Count	35.861	49.705	0	250
Klipfontein Daily Case Count	47.839	53.722	0	201
Tygerberg Daily Case Count	84.179	107.722	0	549
Southern Daily Case Count	82.448	112.293	0	580
Mitchells Daily Case Count	49.891	60.891	0	290
Eastern Daily Case Count	74.133	98.323	0	483
Northern Daily Case Count	55.042	78.492	0	393
Western Daily Case Count	81.239	109.917	0	544

Weather averages calculated across seven weather stations: Kirstenbosch, Jonkershoek, Atlantis, Astronomical Observatory, CapePoint, Slangkop, and Strand. Case data from Western Cape cooronavirus dashboard – see footnote 3.

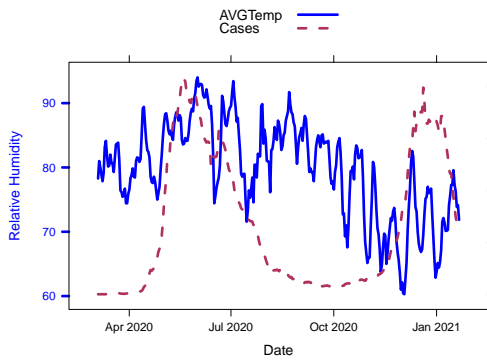


(4.2.1) Low SES

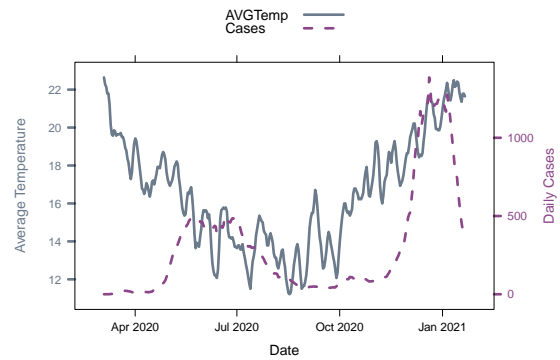


(4.2.2) Middle/High SES

Figure 4.2: Case and temperature data: Seven-day rolling average



(4.3.1) Low SES



(4.3.2) Middle/High SES

Figure 4.3: Case and relative humidity data: Seven-day rolling average

4.4.2 Model choice

A pre-analysis process was used to focus our attention on one set of results. As implied earlier, we estimated numerous models, selecting the model that minimised the Akaike Information Criterion (AIC). The results of that modelling exercise are presented in Table 4.3; the table lists the AIC for the various models estimated. As is clear from the table, models including day of week, month, 21 days of lag, along with the lock-down, as scheduled, minimised AIC; furthermore, including both temperature and humidity effects was also desirable, based on the AIC criteria.

Table 4.3: Akaike information criterion (AIC) for multivariate lag humels

	Temperature	Humidity	Both
21 day lag only	391722.6	436084.4	244664.6
With Day of Week	296786.3	338277.4	164237.6
Lockdown as scheduled	118233.6	124339.1	53872.0
One week lockdown lead	118075.5	116034.6	57890.3
One week lockdown lag	133438.3	165640.8	68238.3

Akaike information criterion calculated from quasi-poisson models relating one meteorological control - temperature, humidity or both (accounting for 21 day lag), to the daily case count in the city of Cape Town. All lockdown models also include day of the week fixed effects.

4.5 Exposure-response estimates

Below, the association between daily temperature or relative humidity and daily Covid-19 cases is presented in two and three dimensional graphs. The 3-D graphs present the complete association between weather, relative risk (of reporting a case) and the lag structure. Thus, 2-D figures can represent slices with lags or weather. Visual inspection of these figures indicates that the associations are nonlinear for both meteorological factors across the lag range (0-21 days).

4.5.1 Covid-19 cases in low socioeconomic areas

We begin with an analysis of the daily cases in low SES areas, starting with the overall relationships for temperature and humidity, respectively, in Figures 4.4 and 4.5. From these figures, we see peak cases at temperatures just below 15°C and humidity around 55%. However, statistical significance – compared a relative risk of one – is only uncovered near the humidity peak; we do not find any statistically significant temperature effects in this temperature figure.

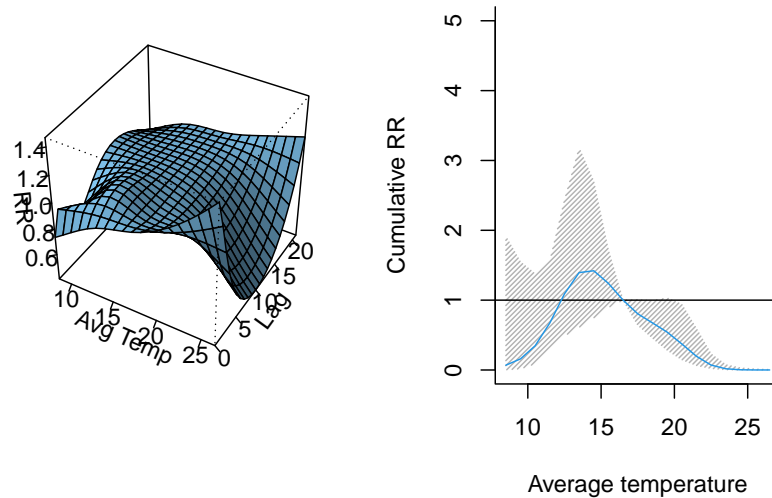


Figure 4.4: Effects of temperature on daily Covid-19 cases in LSE

We further dissect the results, looking at upper (90^{th}) and lower (10^{th}) quantiles of the weather data. Figures 4.6 and 4.7 present these for temperature and humidity, respectively. Although we did not find statistical significance for temperature, above, shifting attention to the lag structure, we do. Especially for relatively high temperatures (21°C), where relative case risk is statistically significantly lower during the second week of the lag, i.e., day 7 to 14. On the other hand, at low temperatures, we do not find any statistically significant lag structure. Regardless of whether we consider low or high humidity, there is some evidence that, at short lags (< 5 days), relative risk decreases (statistically significantly so).

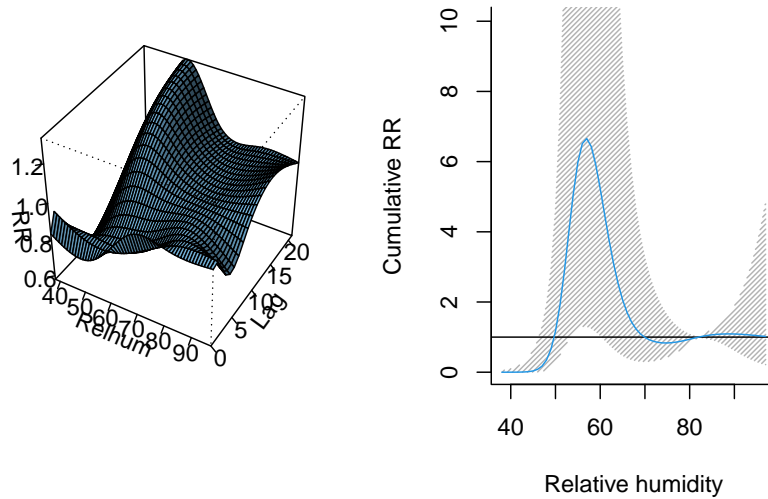


Figure 4.5: Effects of relative humidity effect on daily Covid-19 cases in LSE

However, at the 10th quantile of humidity, case risk is increasing at longer lags (from the beginning of the second week to the end of the lag period).

4.5.2 Covid-19 cases in middle/high socioeconomic areas

Next, we turn our attention to sub-districts in the city that are, on average, better off. As above, Figures 4.8 and 4.9 offer the 3-D and 2-D weather effects for temperature and relative humidity, respectively. In the middle to high SES areas, there is no statistically significant temperature effect associated with temperature. On the other hand, there is a statistically significant (and large) positive case risk associated with relatively low humidity.

Potential differences in lag-response-curves are presented in Figures 4.10 and 4.11. These consider the relative risk for temperature and relative humidity across the lag structure at the 10th and 90th percentiles of temperature and relative humidity. In the case of low temperatures, there are statistically significant positive lag effects near the second week. There is also evidence of statistically significant positive lag effects at higher temperatures; however, those are limited to about the first 10 lags. After that, lag effects turn negative,

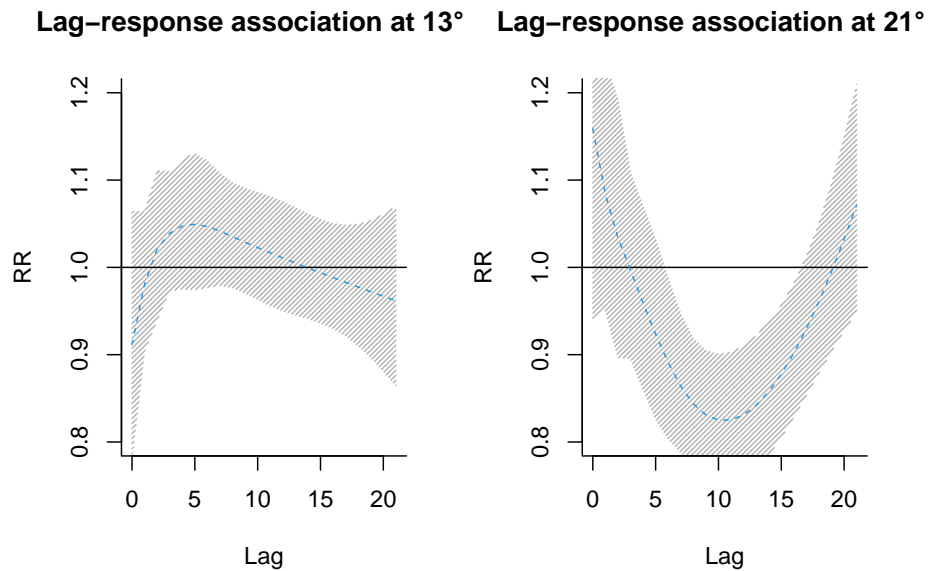


Figure 4.6: The estimated effects of relatively cold and hot temperatures over the 21-day lag on recorded Covid-19 cases in low SES areas

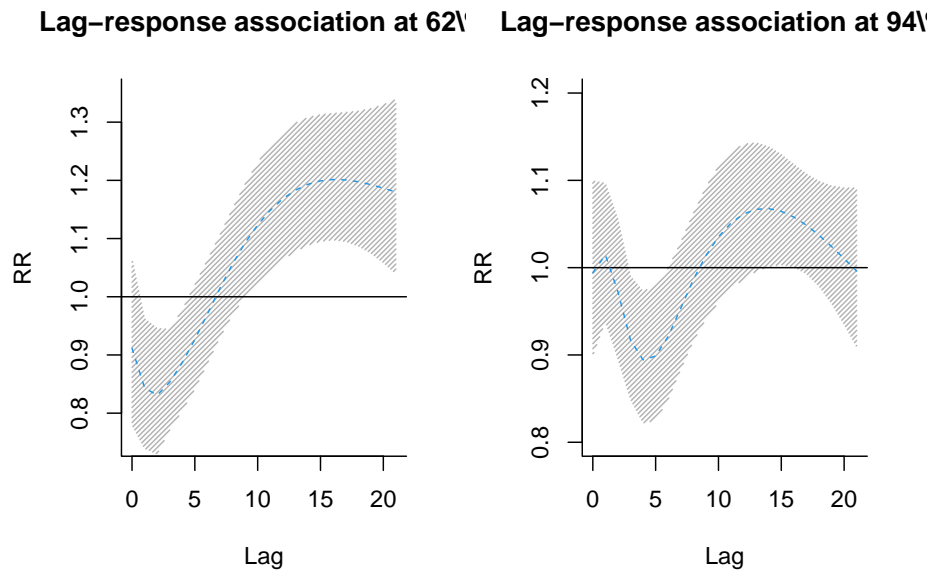


Figure 4.7: The estimated effects of relatively low and high humidity over the 21-day lag structure on recorded Covid-19 cases in low SES areas

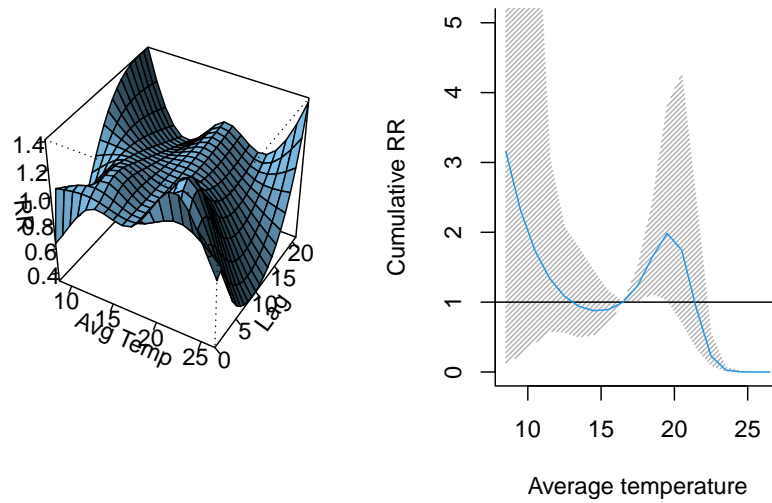


Figure 4.8: Effects of temperature on daily recorded Covid-19 cases in middle to high SES areas

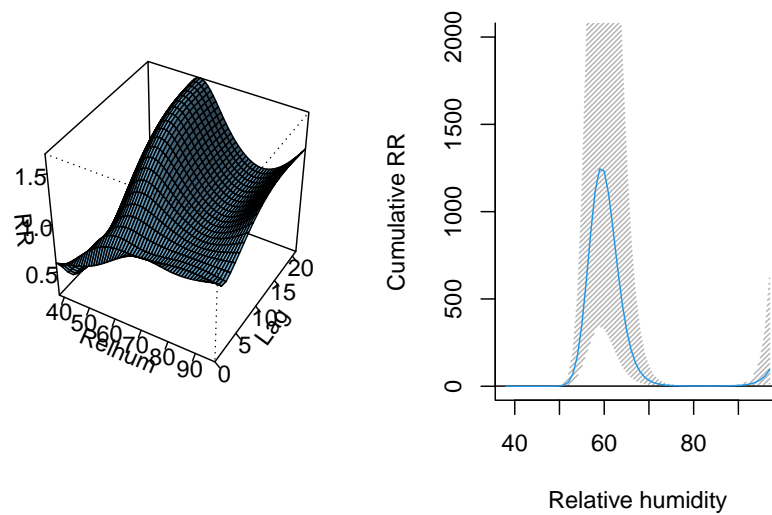


Figure 4.9: Effects of relative humidity effect on daily recorded Covid-19 cases in middle to high SES areas

reducing the case risk after approximately lag 10. In the case of relative humidity, we see extensive differences compared to the low SES areas. In particular, regardless of whether we consider low or high relative humidity, there is evidence that after a few lags, case risk increases markedly for the remainder of the lag period. That is, after one week, prolonged exposure to humidity in the middle to higher SES regions of the city led to an increase in case risk.

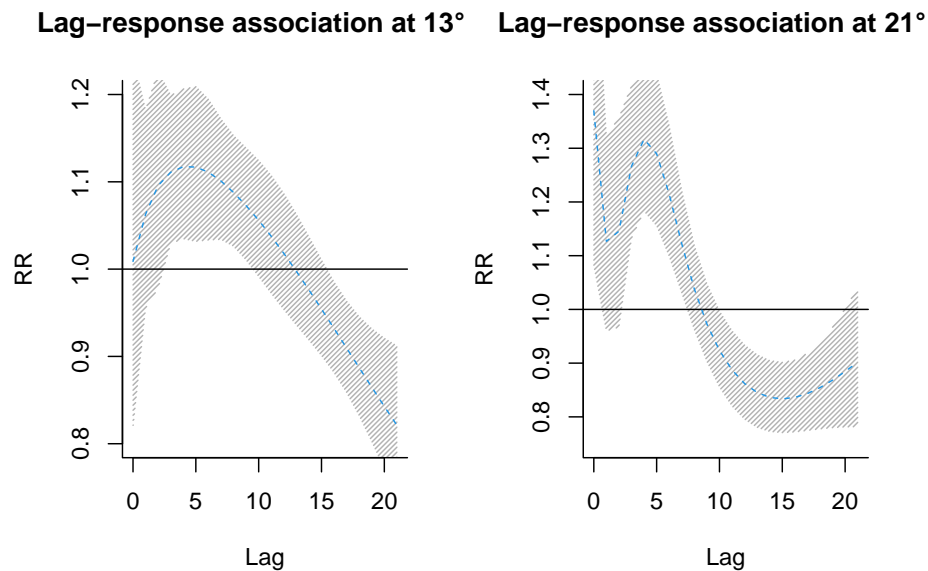


Figure 4.10: The estimated effects of relatively cold and hot temperatures across the 21-day lag period on recorded Covid-19 cases in middle to high SES areas

4.5.3 Lock-down measures

As previously noted, the DLNM model included various additional controls: lock-down measures, as well day of the week fixed effects. Table 4.4 and 4.5 present the coefficients for the lock-down measures included in the different DLNM models for LSES and MHSES areas, respectively. In general, lock-down is associated with more recorded cases, with lock-down level 5 (actual) being the only negative estimate (and that estimate is relative to no lock-down). Furthermore, with the exception of the actual level 5 and level 2 estimates,

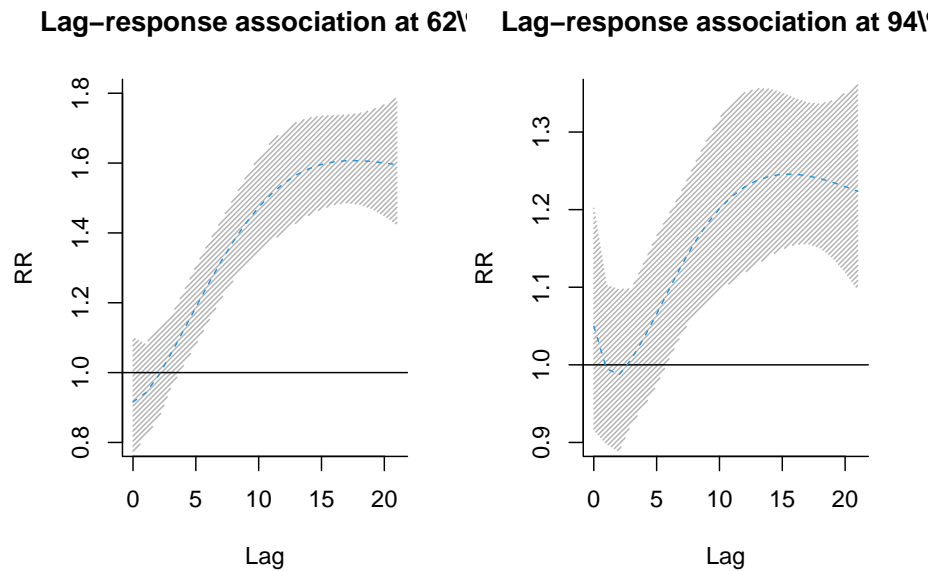


Figure 4.11: The estimated effects of relatively low and high humidity across the 21-day lag period on recorded Covid-19 cases in middle to high SES areas

the coefficients were higher in low SES areas. The larger low SES coefficients correspond to the recorded cases in Figures 4.2 and 4.3, which show a lower first peak in the middle to high SES areas of the city, but otherwise similar second peak levels.

Although government initiated lock-down to reduce cases, the results suggest that lock-down was not associated with case reduction. With respect to interpretation, it is important to recall that lock-down levels were determined by government, and the decisions on lock-down were made at the highest level of government. Thus, lock-down cannot realistically be assumed to be exogenous. Given differences in density, and access to fresh water, and either local or household sanitation differences, we anticipated differences across the SES status regions. In wealthy sub-districts, residents may have been more likely to work from home, finding it easier to adhere to the lock-down measures, by reducing mobility or otherwise following the promoted health protocols. Conversely, in overcrowded townships, such as Khayelitsha, compliance would not be as easy to manage, due to limited living space and inadequate access to basic services.

Table 4.4: Association between lock-down and recorded cases in low SES areas of Cape Town

Variables	Actual	One week lead	One week lag
	Estimates	Estimates	Estimates
Lock-down 1	NA	0.5998 (3.070)	5.5113 ^a (1.854)
Lock-down 2	0.0146 (0.252)	0.5009 (3.070)	5.3519 ^a (1.856)
Lock-down 3	2.0048 ^a (0.173)	3.1167 (3.063)	7.2507 ^a (1.844)
Lock-down 4	1.6335 ^a (0.191)	3.2151 (3.060)	7.5840 ^a (1.839)
Lock-down 5	-2.3146 ^a (0.293)	0.0165 (3.062)	5.0613 ^b (1.841)

Coefficients and HC1 corrected standard errors for each level of lock-down in the (low SES) DLNM models. Actual refers to the actual dates of each level, while lead effectively moves the lock-down dates one week earlier and lag moves the dates one week later. ^a - statistical significance at least 0.001; ^b - statistical significance at least 0.005.

4.6 Discussion

Recent reviews report mixed findings, when it comes to the effects of temperature and relative humidity on Covid-19 incidence and mortality, globally (Mecenas et al. 2020; McClymont and Hu 2021; Dong et al. 2021; Weaver et al. 2022). Many previous studies assumed a linear association or used methods, such as simple correlation analysis (Mecenas et al. 2020; McClymont and Hu 2021; Dong et al. 2021; Weaver et al. 2022). Thus, the heterogeneity in results could be attributed to differences in statistical approach. Our results suggest that such methods are not likely to capture the inherent relationship between the environment and disease transmission, especially if there are inherent lags in that relationship. In that regard, our results are similar to other research applying DLNMs: in four European countries (Fu et al. 2021); eight cities in the USA (Runkle et al. 2020); Wuhan, China (Zhu et al. 2021); low- and middle-income countries (LMICs), such as Brazil, Mex-

Table 4.5: Association between lock-down and recorded cases in middle to high SES areas of Cape Town

Variables	Actual	One week lead	One week lag
	Estimates	Estimates	Estimates
Lock-down 1	NA	0.0806 (1.516)	3.3633 ^a (0.732)
Lock-down 2	-0.4580 ^d (0.241)	-0.7328 (1.521)	2.5362 ^a (0.750)
Lock-down 3	1.3596 ^a (0.160)	1.5597 (1.508)	4.2094 ^a (0.728)
Lock-down 4	0.5962 ^a (0.187)	1.5762 (1.501)	4.6483 ^a (0.705)
Lock-down 5	-2.7922 ^a (0.313)	-1.5642 (1.506)	2.1234 ^a (0.715)

Coefficients and HC1 corrected standard errors for each level of lock-down in the (middle to high SES) DLNM models. Actual refers to the actual dates of each level, while lead effectively moves the lock-down dates one week earlier and lag moves the dates one week later. ^a - statistical significance at least 0.001; ^d - statistical significance at least 0.1.

ico, Pakistan, Peru, Russia, Ukraine, India, Thailand, and China (Wang et al. 2023); and 12 Italian Cities (Fong and Smith 2022). Differences between Runkle et al. (2020), Zhu et al. (2021), Fu et al. (2021), Fong and Smith (2022) and Wang et al. (2023) and us are likely related to differences in study locations.

The SARS-CoV-2 virus is more stable in a combination of cold and dry temperatures, because respiratory droplets, containers of viruses, remain in suspension longer in dry air (Aboubakr, Sharafeldin, and Goyal 2021; Nottmeyer et al. 2023). Our results generally support the notion that case risk is higher, when conditions are dryer, regardless of SES area. Higher humidity may raise atmospheric suspended matter, the volume of virus deposited on surfaces, and virus survival time in respiratory droplets that sit on surfaces (Paynter 2015; Aboubakr, Sharafeldin, and Goyal 2021). Our results also suggest that very high levels of humidity are not associated with increased case risk, in agreement with research suggest-

ing that higher relative humidity can increase the size of aerosols, limiting suspension time in the air, which would retard Covid-19 transmission (Aboubakr, Sharafeldin, and Goyal 2021; Wang et al. 2023).

Our results also suggest that the cumulative relative risk is not affected by temperature. Although previously noted literature suggests virus stability in cold temperatures, E. G. Hanna and Tait (2015) suggests that low temperatures offer ideal survival and reproduction conditions for viruses, because cold air leads to vasoconstriction of the respiratory tract, which may weaken the immune system. Similarly, cold air may cause small raptures in the nasal mucosa and slowing of mucociliary clearing, thus inhibiting the innate immune response. More recent research also suggests the exact relationship is not so simple, and, thus, is also likely to depend on the host (Mecenas et al. 2020; Mcclymont and Hu 2021; Runkle et al. 2020; Zhu et al. 2021; Islam, Abul, and Azad 2021; Fu et al. 2021). The innate immune response is crucial in counteracting initial infection, hampering viral replication, and mediating the strength of the immune response and severity of inflammation (L. F. García 2020).

Our results also suggest rather complicated relationships between the host and temperature responses. We find differences in temperature lags across the SES sub-districts. In middle to high SES regions, regardless of whether we considered high or low temperatures, at small lags, case risk increased. At rather long lags and high temperatures, heat was found to be protective, reducing the case risk. In low SES areas, temperature was protective, but only during the second week of the three week lag period, and only at high temperatures. Initially, we expected bigger differences across SES groups, with respect to the effects of the environment. However, even informal housing, which is mostly made from sheets of corrugated iron, bricks, wood and plastic, and are poorly insulated protect better against the cold than the heat (Scovronick and Armstrong 2015).

An advantage of this study is that it addressed design limitations identified in recent reviews

(Mecenas et al. 2020; Mcclymont and Hu 2021; Dong et al. 2021; Weaver et al. 2022) through DLNMs. Thus, the nonlinear and cumulative effects of temperature and relative humidity were investigated simultaneously. We also accounted for confounders, such the government lock-down levels and daily differences in testing activities. Additionally, this research was conducted in a developing country, where socio-economic factors might be expected to influence disease transmission (Baker et al. 2020).

Although there are advantages associated with this research, there are also some limitations. Meteorological data is measured at a few fixed locations, so there may be exposure misclassification; potentially biasing estimates towards the null (Hatchl and Thomas 1993). We also used recorded case data, as a proxy for actual cases. Mcclymont and Hu (2021) note that confirmed case data is dependent on the accuracy, availability and quality of the testing. In addition, it should be noted that financial issues, or simple “need” for tests, could influence the number of tests, and, therefore, recorded cases. Furthermore, these may not be homogeneous across SES regions, which may create large discrepancies between the actual number of cases and test-confirmed cases. Although our modelling approach made use of lagged effects associated with temperature and humidity, we did not attempt to address lag effects related to test-seeking, which could lead to additional biases, although correcting for selection and measurement error is not plausible with the data that we have. However, we did attempt to address this last concern through the application of different lag periods; our statistical testing suggests that longer lag periods were more appropriate for the analysis. Finally, it should be noted that we did not have data that would allow us to more directly address different social determinants of health (e.g., gender, race and ethnicity, occupation) to allow for a further examination of their association with Covid-19 transmission.

4.7 Conclusion

In this research, we examined the relationship between the environment and health, focusing on reported cases of Covid-19 in the city of Cape Town. The empirical exercise was based on dynamic non-linear lag models, including up to 21-day lags for temperature and relative humidity, along with day of week fixed effects, lock-down control measures, and a separate analysis for low vs middle to high SES areas in the city. The results indicate a complex association between Covid-19 incidence, temperature, relative humidity, and socioeconomic status. Case risk was lowest for relatively low humidity days, and was not significantly altered by temperature, except through lags. Finally, we uncovered differences in the case-weather-response mechanism across the SES regions we were able to consider.

5 Chapter V: Conclusion

Climate change affects human health directly and indirectly. Direct pathways include extreme temperatures that can lead to heat-related illnesses and changes in precipitation patterns leading to floods and droughts, increasing the spread of vector-borne diseases. It indirectly affects health in several ways as changes in rainfall patterns can lead to water scarcity, increasing the risk of malnutrition due to reduced food production and waterborne diseases. Moreover, it increases the frequency and intensity of natural disasters, which can disrupt healthcare systems and lead to physical and mental health issues. Furthermore, economic disruptions occurring in weather-sensitive industries can impact health by increasing stress, anxiety, and depression, due to the loss of livelihoods.

Research on the impact of climate change on health in developing countries remains sparse, despite the recent uptick. This thesis aimed to deepen our understanding of the link between climate and health in the context of (at least two) developing countries. We use data from Kenya to analyse the impact of drought on child health. Our focus is due at least in part to the fact that over 80% of the country's land is classified as Arid and Semi-Arid Land, while drought is the most common natural occurrence. Furthermore, we use data from South Africa to analyse the temperature-humidity-socioeconomic status nexus in the transmission of covid cases. The country's large Gini coefficient, which arose out of a historically highly segregated socioeconomic structure that persists to this day, provides a basis upon which to explore the socioeconomic disparity component of the aforementioned nexus, which has not received much attention in the literature, as far as we can determine.

The thesis contains three analytical chapters considering climate, women socioeconomic status and child health in Kenya, as well as covid cases in South Africa. In our analysis of the long-term impacts of drought on women and their offspring, we link data from the Demographic and Health Survey, accessed through Integrated Public Use Microdata Series database and climate data from the renowned Climate Research Unit's Time-Series. We ex-

amine the impacts of rainfall fluctuations on women health and socioeconomic status then explore whether these effects are transmitted to their children child aged 0 - 59 months in Kenya. We further explore the opposite possibility that positive rainfall shocks might enable low birth weight children to “catch up” in growth and develop similarly to children with normal birth weight. We use cumulative rainfall measures of distinct natural experiments to identify the impact of early life shocks in different regions and years. This research also considers socioeconomic status as a potential mediator through which climate effects are transmitted to the next generation in rural households. Finally, we use anonymised daily COVID-19 case data obtained from the Western Cape province COVID-19 dashboard for the period covering 1 March 2020 to 24 January 2021, which we combined with meteorological data from the South African Weather Service. The combined data was used to explore the association between climate and the incidence of COVID-19 in Cape Town, while distinguishing between low and high socio-economic status sub-districts.

The thesis has attempted to answer three questions. First, what are the long-term impacts of drought on women, and could these impacts be transmitted to their children? Second, can positive rainfall shocks mitigate or even reverse the adverse health effects for low birth weight children? Third, what is the relationship between meteorological, socioeconomic factors and the transmission of COVID-19?

In trying to examine the long-term impacts of drought on women’s adult outcomes and child health, we focused on rainfall deficits experienced during early life, including the *in utero* period. Our results show that cumulative drought exposure during a woman childhood is negatively associated with wealth, years of education and weight. Moreover, children born to mothers who experienced drought decades earlier are more likely to have a low birth weight and an increased probability of being underweight. Additionally, our findings suggest that boys are affected by rainfall deficit while *in utero* and are at risk of being underweight whereas the effects of drought on girls appear to be mixed. In trying to address potential rainfall deficit mechanisms, we applied simple mediation analysis to investigate

whether socioeconomic status is a mechanism through which long-term drought effects are transmitted to young children. Hence, we found that drought negatively impacts women's health and socioeconomic outcomes, with these effect being transmitted to their children.

To consider whether positive rainfall shocks could support catch-up growth in LBW children, we leveraged the fact that in Arid and semi-arid lands (ASALs), positive rainfall is a beneficial event. Our findings indicate that low birth weight (LBW) children may achieve catch-up growth in both absolute (WAD) and relative (WAZ) dimensions even beyond the age of two years. One concern that arises in a study like this is the potential for endogeneity – specifically, that other parental behaviours or child factors could relate to both catch-up and rainfall – to either bias the results or impact the interpretation. However, rainfall shocks can assumed to be randomly distributed, and, therefore, we interpret the effect of rainfall on catch-up to be causal, while acknowledging that these unobserved factors might be catch-up growth enhancing or detrimental to catch-up growth. We also control for observed confounders. Thus, we also show that mother's weight and height are positively associated with catch-up growth, but the magnitude remains small. Birth order is statistically significant, negatively impacting the probability of catch-up. Mother's education is positively associated with the probability of catch-up in the case of positive WAZ, but it also remains insignificant. Finally, wealth, as measured by an index, is statistically associated with positive catch-up.

In our final analysis, we consider the general relationship between climate and the incidence of one of the most deadly viruses to affect the world in decades. We further that analysis to see whether that relationship appears to vary along socioeconomic dimensions. The city of Cape Town is an ideal location for the analysis, given data availability, as well as clear socioeconomic district borders. We find a complex association between Covid-19 incidence, temperature, relative humidity and socioeconomic status. Those living in the middle/high socio-economic status areas seem to be more vulnerable to cold effects than those in low socio-economic status areas. Heat significantly lowered the risk of Covid-19

incidence in the low socio-economic status. In contrast, heat increased the risk in middle/high socio-economic status areas. Dryness significantly decreased the risk of Covid-19 incidence. The risk arising from humid conditions, in general, increased with longer lags in all the areas and was significant in the middle/high Socio-Economic Status areas for the lag period considered.

This study has limitations. First, our analysis of catch-up growth in low birth weight (LBW) children and the role of positive rainfall shocks in mitigating adverse health effects was constrained by a limited sample size. According to the World Health Organization (WHO), LBW is defined as a birth weight below 2,500 grams. However, due to a high attrition rate in the 2014 Kenya Demographic and Health Survey (DHS) dataset, only about 28% of children had recorded birth weights, resulting in a small sample of LBW children. To address this, we pooled data from five rounds of the Kenya DHS to examine catch-up growth up to ages two and beyond. For the analysis of impact of positive rainfall shocks, only the 2014 DHS round contained district-level information, necessitating a focus on that dataset. To increase the sample size of LBW, we included in the analysis children with a birthweight $\leq 2,500$ grams which is closer to the UNICEF definition and reported the findings for both groups. Future studies with larger samples of LBW children are needed to enhance the generalizability of our findings.

Second, for the association between climate and Covid-19 analysis, meteorological data is measured at a few fixed locations, so there may be some inevitable exposure misclassification. Also, confirmed covid-19 cases data may have limitations due to issues with quality and accuracy of tests in addition to the availability of testing. This may create discrepancies between the actual number of cases and test-confirmed cases due to bias introduced by using date of case reported and not accounting for the lag or delay between the recorded date of a positive test and initial symptom onset or exposure. In this study, the possible bias was addressed by statistical modelling with varying lag intervals to account for incubation periods.

Thus, although no research project is perfect, we believe that we have answered all of the questions we have posed. We have found strong correlations between health and climate, supporting a relatively wide and growing literature concerned with these impacts. We believe that in the developing world especially in arid and semi-arid regions, climate variability poses a significant threat to large segments of the population. Climate change is expected to intensify these challenges, with rising temperatures and increasing fluctuations in precipitation patterns. These changes heighten vulnerability and risk, particularly among already marginalized communities. As such, there is a pressing need for interventions that enhance community resilience to climate stress, with the aim of disrupting cycles of inter-generational health inequality and safeguarding the well-being of future generations.

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A Appendix

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B Appendix for Chapter 2

B.1 Kenya Map

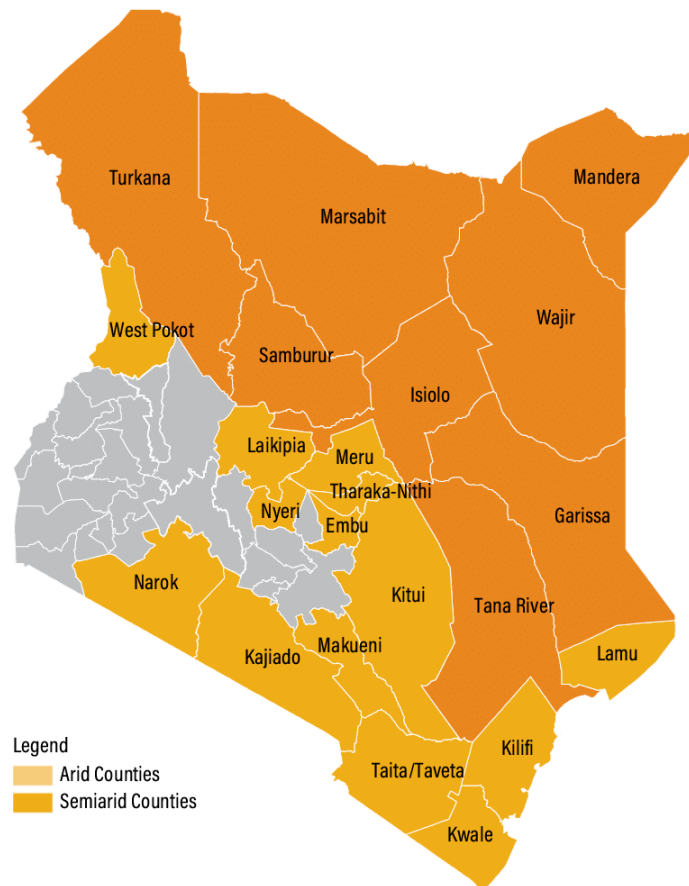


Figure B.1: Kenya Map, Source:Chaudhury et al., 2020

B.2 Impact of drought on child health

Table B.1: Long term impact of drought on child wasting

	Model 1	Model 2	Model 3
Panel A: Females			
Cumulative severe drought ($t - 1 : t + 4$)	0.0100 (0.045)	0.0019 (0.045)	-0.0212 (0.050)
Cumulative severe drought1 ($t : t + 4$)	0.0045 (0.042)	-0.0022 (0.043)	-0.0323 (0.044)
Cumulative moderate drought ($t - 1 : t + 4$)	0.0043 (0.020)	0.00009 (0.021)	-0.0196 (0.021)
Cumulative moderate drought1 ($t : t + 4$)	0.0033 (0.020)	-0.00009 (0.020)	-0.0175 (0.020)
Panel B: Males			
Cumulative severe drought ($t - 1 : t + 4$)	0.0162 (0.051)	0.0125 (0.052)	0.0056 (0.053)
Cumulative severe drought1 ($t : t + 4$)	-0.0010 (0.050)	-0.0045 (0.050)	-0.0294 (0.050)
Cumulative moderate drought ($t - 1 : t + 4$)	-0.0007 (0.023)	-0.0041 (0.023)	-0.0189 (0.024)
Cumulative moderate drought1 ($t : t + 4$)	-0.0124 (0.022)	-0.0154 (0.022)	-0.0289 (0.023)

Severe drought implies an $SPI < -1.5$ and $SPI < -1$ for moderate . Dependent variable is underweight; cluster robust standard errors (clustered at household level) in parentheses. All estimates are for rural mothers. Model 1 includes Mother's age, year of birth fixed effects and place of birth fixed effects. Model 2 adds religion and Model 3 includes ethnicity

Table B.2: Impact of drought on child birthweight (low birthweight)

	Model 1	Model 2	Model 3
Panel A: Females			
Cumulative severe drought ($t - 1 : t + 4$)	-0.2244 (0.211)	-0.2800 (0.211)	-0.3558 (0.219)
Cumulative severe drought1 ($t : t + 4$)	-0.1403 (0.187)	-0.1775 (0.185)	-0.2543 (0.193)
Cumulative moderate drought ($t - 1 : t + 4$)	0.0237 (0.106)	0.0069 (0.106)	-0.0127 (0.103)
Cumulative moderate drought1 ($t : t + 4$)	0.0131 (0.092)	0.0002 (0.092)	-0.0205 (0.087)
Panel B: Males			
Cumulative severe drought ($t - 1 : t + 4$)	0.0433 (0.192)	0.0331 (0.193)	0.0579 (0.205)
Cumulative severe drought1 ($t : t + 4$)	0.1131 (0.203)	0.1102 (0.203)	0.1172 (0.212)
Cumulative moderate drought ($t - 1 : t + 4$)	0.1188 (0.107)	0.1121 (0.106)	0.1621 (0.108)
Cumulative moderate drought1 ($t : t + 4$)	0.1002 (0.087)	0.0954 (0.086)	0.1264 (0.087)

Severe drought implies an SPI < -1.5 . Dependent variable is LBW; cluster robust standard errors (clustered at household level) in parentheses. All estimates are for rural mothers. Model 1 includes number of children under 5 in the household, number of children ever born, Mother's age, year of birth fixed effects and Province of birth fixed effects. Model 2 adds variables such mother's height and weight. Model 3 includes ethnicity and religion

C Appendix for Chapter 3

C.1 Impact of positive rainfall shock on catch-up growth of LBW Children

Table C.1: Impact of positive rainfall shock on catch-up growth of LBW Children (<2500g) up to 2 years

	Positive WAZ		Positive WAD	
	(1)	(2)	(3)	(4)
Birth order	0.026 (0.078)	0.027 (0.080)	0.023 (0.081)	0.022 (0.079)
Children under 5	-0.383 * * (0.167)	-0.380 * * (0.169)	-0.373 * * (0.168)	-0.379 * * (0.166)
Mother Height	0.018 (0.024)	0.018 (0.024)	0.016 (0.024)	0.019 (0.024)
Mother weight	0.004 (0.015)	0.004 (0.015)	0.003 (0.015)	0.004 (0.015)
Mother Education	-0.024 (0.054)	-0.024 (0.056)	-0.028 (0.058)	-0.021 (0.055)
Ethnicity	0.019* (0.011)	0.019* (0.011)	0.018* (0.011)	0.020* (0.010)
Wealths	0.833 * ** (0.322)	0.840 * ** (0.312)	0.870 * ** (0.319)	0.847 * ** (0.309)
Mild moisture	-0.062 (0.865)			
Moderate moisture		-0.048 (0.887)		
Exceptional moisture			-0.822 (0.907)	
Extreme Moisture				-1.041 (0.833)
Num.Obs.	386	386	386	386
F	26.816	26.250	26.431	26.280
RMSE	0.21	0.21	0.21	0.21
Std.Errors	HC1	HC1	HC1	HC1

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAZ and WAD; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weight < 2500 grams. The sample is from the 2014 DHS survey. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2: Impact of positive rainfall shock on catch-up growth of LBW Children up to 4 years

	Positive WAZ		Positive WAD	
	(1)	(2)	(3)	(4)
Birth order	0.028 (0.079)	0.027 (0.080)	0.022 (0.081)	0.022 (0.079)
Children under 5	-0.375 ** (0.170)	-0.379 ** (0.169)	-0.367 ** (0.170)	-0.380 ** (0.166)
Mother Height	0.018 (0.024)	0.018 (0.024)	0.016 (0.024)	0.019 (0.024)
Mother weight	0.003 (0.015)	0.004 (0.015)	0.003 (0.015)	0.003 (0.015)
Mother Education	-0.025 (0.054)	-0.025 (0.056)	-0.033 (0.059)	-0.022 (0.056)
Ethnicity	0.019* (0.011)	0.019* (0.011)	0.017 (0.011)	0.019* (0.010)
Wealths	0.843 *** (0.316)	0.841 *** (0.311)	0.889 *** (0.320)	0.851 *** (0.307)
Mild moisture	0.082 (0.830)			
Moderate moisture		-0.058 (0.903)		
Exceptional moisture			-1.084 (0.939)	
Extreme Moisture				-1.299 (0.884)
Num.Obs.	386	386	386	386
F	27.168	26.377	26.779	26.479
RMSE	0.21	0.21	0.21	0.21
Std.Errors	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>	<i>HC1</i>

The dependent variable is the catch-up growth in weight expressed as the positive variation in WAZ and WAD; standard errors are in parentheses. Estimations include cumulative rainfall variables, mother and child characteristics, household composition and socioeconomic variables. The dataset include children with birth weight < 2500 grams. The sample is from the 2014 DHS survey. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$