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# Health and Welfare Implications of Climate Variability

## Evidence from Rural Uganda

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# Abstract

Uganda has been highly affected by extreme weather events and climate change in the recent years. Weather-related disasters could potentially affect health outcomes directly, or indirectly through its deleterious effects on water resources, and agriculture which are the main sources of livelihoods for rural households. Despite growing interest in climate-health research, empirical studies on the effects of climate variability on health, especially the indirect effects and health adaptation, with a gender lens in developing countries remains scanty.

The study begins by tracing the causal pathways of extreme weather events on child health using four waves of national representative data. Results from simultaneous equation models show evidence of significant negative effects of droughts and heatwaves on the quantity and quality of production, which in turn affect child health as measured by anthropometrics. Most detrimental effects are through seasonal drought which reduces crop yield, calorie, protein and zinc supply by up-to 85%, 59% 34% and 29% respectively. On the other hand, zinc has a larger effect on height-for-age z-scores (HAZ), weight-for-age z-scores (WAZ) and weight-for-height z-scores (WHZ). A 10% decrease in zinc reduces HAZ by 0.06 standard deviations (SD) and weight outcomes by 0.08 SD. Although boys HAZ are more sensitive to nutrient deficiencies compared to girls HAZ, nutrients largely influence girls WHZ. Further results show a positive effect of livestock holding on weight measures, while diarrhoea leads to poor HAZ and WAZ.

Secondly, the study assesses the gender differentiated health effects of weather variability using two-parts and nonlinear decomposition models. The study finds that low rainfall below the long-term mean increases the likelihood of illness and work days lost significantly by at least 8 and 6 percentage points in women and men respectively, whereas warming increases illness by around 2-5 percentage points. The indirect effect of low rainfall on illness through the water collection pathway is significant only in women, estimated at 0.2 percentage points, implying full mediation process. Further results reveal that 27%-57% of women-men health inequalities would be eliminated if endowments, especially health care are equalized.

Finally, the short-term effects of weather and health shocks and their interactions on household consumption are estimated using six waves of a recent high frequency panel dataset. Fixed effects results show that food consumption and diet diversity are unaffected by illness. However, extremely high rain reduces all consumption groups by 11-14%. Quantile estimates show that poor households exposed to extreme temperature and more sick days reduce their non-food consumption significantly, while hospitalization increases non-food at the top quantile by 13%. Health shocks and extreme wetness increase health expenditures while labour remain unaffected by illness, despite being negatively affected by extreme temperatures. Intake of diverse animal foods, fruits and vegetables are associated with better health.

This dissertation concludes by highlighting key adaptation strategies that can inform policy makers. Interventions that facilitate credit access, savings, market access, safety nets and good agronomic practices could increase household resilience thus improved food security and health. Moreover, households should engage in non-farm work and livestock farming since livestock is fairly adaptable and intake of diverse animal products could help mitigate the adverse effects extreme weather events on health. The heterogeneous effects of group networks and remittances on consumption across quantiles imply the need for proper targeting of measures to be beneficial to intended groups, together with women empowerment efforts.

# Zusammenfassung


## Auswirkungen der Klimavariabilität auf Gesundheit und Wohlbefinden: Evidenz aus dem ländlichen Uganda

Uganda war in den letzten Jahren stark von extremen Wetterereignissen und dem Klimawandel betroffen. Witterungsbedingte Katastrophen könnten sich direkt oder indirekt durch ihre schädlichen Auswirkungen auf die Wasserressourcen und die Landwirtschaft, die die Haupteinnahmequellen der ländlichen Haushalte darstellen, auf die Gesundheit auswirken. Trotz des wachsenden Interesses an der Klima-Gesundheits-Forschung gibt es nur wenige empirische Studien zu den Auswirkungen von Klimaschwankungen auf die Gesundheit, insbesondere zu den indirekten Auswirkungen und zur gesundheitlichen Anpassung unter Berücksichtigung der Geschlechterperspektive in Entwicklungsländern.

Die Studie beginnt mit der Verfolgung der kausalen Pfade von extremen Wetterereignissen auf die Gesundheit von Kindern unter Verwendung von vier Wellen von national repräsentativen Daten. Die Ergebnisse von Simultangleichungsmodellen zeigen signifikante negative Auswirkungen von Dürren und Hitzewellen auf die Quantität und Qualität der Produktion, die sich wiederum auf die anthropometrisch gemessene Kindergesundheit auswirken. Die meisten negativen Auswirkungen hat die saisonale Dürre, die den Ernteertrag, die Kalorien-, Protein- und Zinkversorgung um bis zu 85 %, 59 %, 34 % bzw. 29 % verringert. Andererseits hat Zink eine größere Auswirkung auf den Z-Wert der Körpergröße im Alter (HAZ), den Z-Wert des Gewichts im Alter (WAZ) und den Z-Wert des Gewichts in der Höhe (WHZ). Eine 10-prozentige Abnahme des Zinkgehalts verringert die HAZ um 0,06 Standardabweichungen (SD) und die Gewichtsergebnisse um 0,08 SD. Obwohl die HAZ von Jungen im Vergleich zu den HAZ von Mädchen empfindlicher auf Nährstoffmängel reagieren, beeinflussen die Nährstoffe die WHZ von Mädchen weitgehend. Weitere Ergebnisse zeigen eine positive Auswirkung der Viehhaltung auf die Gewichtsmaße, während Durchfallerkrankungen zu schlechten HAZ und WAZ führen.

Zweitens werden in der Studie die geschlechtsspezifischen Auswirkungen der Wettervariabilität auf die Gesundheit anhand von zweigeteilten und nichtlinearen Zerlegungsmodellen bewertet. Die Studie kommt zu dem Ergebnis, dass geringe Niederschläge, die unter dem langfristigen Mittelwert liegen, die Wahrscheinlichkeit von Krankheit und Arbeitsausfall bei Frauen und Männern um mindestens 8 bzw. 6 Prozentpunkte erhöhen, während eine Erwärmung die Krankheit um etwa 2-5 Prozentpunkte erhöht. Die indirekte Auswirkung von geringen Niederschlägen auf die Krankheit über den Weg der Wasserentnahme ist nur bei Frauen signifikant und wird auf 0,2 Prozentpunkte geschätzt, was auf einen vollständigen Vermittlungsprozess hindeutet. Weitere Ergebnisse zeigen, dass 27%-57% der gesundheitlichen Ungleichheiten zwischen Frauen und Männern beseitigt würden, wenn die Ausstattungen, insbesondere die Gesundheitsversorgung, angeglichen würden.

Schließlich werden die kurzfristigen Auswirkungen von Wetter- und Gesundheitsschocks und deren Wechselwirkungen auf den Haushaltskonsum anhand von sechs Wellen eines aktuellen Hochfrequenz-Paneldatensatzes geschätzt. Die Ergebnisse mit festen Effekten zeigen, dass der Lebensmittelkonsum und die Vielfalt der Ernährung nicht durch Krankheiten beeinflusst werden. Extrem starker Regen führt jedoch bei allen

Verbrauchergruppen zu einem Rückgang um 11-14 %. Quantilsschätzungen zeigen, dass arme Haushalte, die extremen Temperaturen und mehr Krankheitstagen ausgesetzt sind, ihren Non-Food-Konsum deutlich reduzieren, während Krankenhausaufenthalte den Non-Food-Konsum im obersten Quantil um 13 % erhöhen. Gesundheitsschocks und extreme Nässe erhöhen die Gesundheitsausgaben, während die Arbeit trotz der negativen Auswirkungen der extremen Temperaturen nicht durch Krankheit beeinträchtigt wird. Der Verzehr von verschiedenen tierischen Lebensmitteln, Obst und Gemüse wird mit einer besseren Gesundheit in Verbindung gebracht.

Abschließend werden in dieser Dissertation wichtige Anpassungsstrategien aufgezeigt, die den politischen Entscheidungsträgern als Orientierung dienen können. Maßnahmen, die den Zugang zu Krediten, Ersparnissen, Märkten, Sicherheitsnetzen und guten agronomischen Praktiken erleichtern, könnten die Widerstandsfähigkeit der Haushalte und damit ihre Ernährungssicherheit und Gesundheit verbessern. Darüber hinaus sollten sich die Haushalte in der außerlandwirtschaftlichen Arbeit und der Viehzucht engagieren, da die Viehhaltung recht anpassungsfähig ist und der Verzehr verschiedener tierischer Produkte dazu beitragen könnte, die negativen Auswirkungen extremer Wetterereignisse auf die Gesundheit abzumildern. Die heterogenen Auswirkungen von Gruppennetzwerken und Geldüberweisungen auf den Verbrauch in den verschiedenen Quantilen machen eine gezielte Ausrichtung der Maßnahmen erforderlich, damit sie den Zielgruppen zugute kommen, zusammen mit den Bemühungen zur Stärkung der Rolle der Frauen.

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## List of Abbreviations

| | |
|---|---|
| 2SLS | Two Stage Least Squares |
| 3SLS | Three Stage Least Squares |
| CBHI | Community Based Health Insurance Schemes |
| CHIRPS | Climate Hazards Group Infrared Precipitation with Stations |
| CMP | Conditional Recursive Mixed Process |
| DALYs | Disability-Adjusted Life Years |
| FEWS NET | Famine Early Warning Systems Network |
| GLM | The Generalized Linear Model |
| HAZ | Height-for-Age Z Scores |
| HNBM | Hurdle Negative Binomial Model |
| IPCC | Intergovernmental Panel on Climate Change |
| IV | Instrumental Variables |
| JMP | Joint Monitoring Program |
| KHB | Karlson, Holm and Breen |
| LICs | Low Income Countries |
| LSMS –ISA | Living Standards Measurement Study - Integrated Surveys on Agriculture |
| MODIS | Moderate Resolution Imaging Spectroradiometer |
| MUAC | Mid-Upper Arm Circumference |
| NB or negbin | Negative Binomial |
| NDCs | Nationally Determined Contributions |
| NDVI | Normalized Difference Vegetation Index |
| NILA | Nutrition Innovation Labouratory Africa |
| OLS | Ordinary Least Squares |
| PCA | Principal Component Analysis |
| RAE | Retinol Activity Equivalents |
| SDGs | Sustainable Development Goals |
| SOPs | Standard Operating Procedures |
| SPEI | Standardized Precipitation–Evapotranspiration Index |
| SSA | Sub-Saharan Africa |
| TLU | Tropical Livestock Units |
| TNB | Truncated Negative Binomial |
| TPM | Two Parts Model |
| UBOS | Uganda Bureau of Statistics |
| UGX | Uganda Shillings |
| UNPS | Uganda National Panel Survey |
| USGS | United States Geological Survey |
| WASH | Water, Sanitation and Hygiene |
| WAZ | Weight-for-Age Z scores |
| WHO | World Health Organization |
| WHZ | Weight-for-height age Z scores |

# Chapter 1: General introduction

## 1.1 Background

Agriculture and health are interlinked, and among key sectors currently affected by extreme weather events[1] and climate change. In fact, the World Health organization (WHO) recognizes climate variability and change as important factors that not only affects human health but also people's livelihoods and general welfare (Commission on Social Determinants of Health (2008); (World Health Organization, 2014). As of 2020, surface temperature increased by 0.98° Celsius (1.76°F) warmer than the average of twentieth century as shown in Figure 1.1, and 1.19˚C (2.14˚F) greater than (1880-1900) average (Lindsey & Dahlman, 2021). Both the hottest year on record (2016) and the six warmest years in a series occurred in the most recent warmest decade on record (2011-2020) (Lindsey & Dahlman, 2021; World Meteorological Organization, 2020). Furthermore, every month in 2020 except December was among the four topmost warmest for the specific months (Lindsey & Dahlman, 2021; National Oceanic and Atmospheric Administration, 2021).

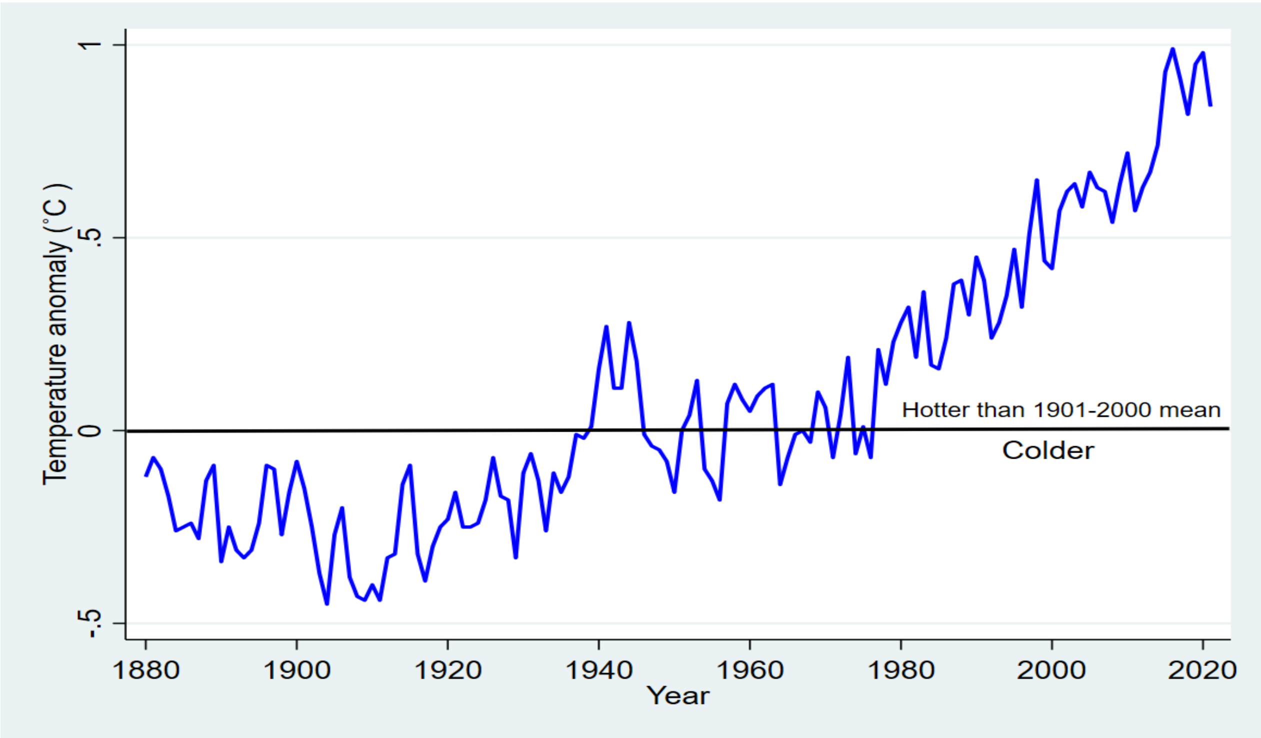


**Figure 1.1**: Annual surface temperature compared to 1901-2000 average, from 1880-2021
Source: Adapted from National Oceanic and Atmospheric Administration (2021)

[1] Intergovernmental Panel on Climate Change (IPCC) (2018) defines both *extreme weather* and *climate events* collectively as "*climate extremes*" which is an occurrence of weather or climate variable value below or above a threshold value near the lower or upper ends of observed variable value range. Extremes are classified also classified under climate variability, defined as average weather or variability in other statistics of temperature or precipitation for a period beyond a month. Classical period is usually 30 years.

Increase in temperature facilitated seasonal temperature extremes and increased rainfall intensity causing flooding in most parts of the world, consequently affecting agriculture, human health, and increasing economic losses. It is estimated that climatic factors contributed to a decline in yield potential of major crops by 1.8-5.6% globally for the time period between 1981 and 2019 (Watts et al 2018). Furthermore, the global disease burden due to climate sensitive illness was estimated at 1.53 billion disability-adjusted life years (DALYS) and deaths related to climate sensitive diseases was approximately 70% of the total annual deaths globally in 2019 (Intergovernmental Panel on Climate Change, 2022). More adverse health impacts of climate are likely to be experienced in the future, affecting individuals in all stages of their lives. For instance, Intergovernmental Panel on Climate Change (2021) projects with high confidence that extreme heat will have critical effects on agriculture and health sectors by mid of 21st century. Furthermore, its projected that in 2030, the number of undernourished people will rise to greater than 840 million (Watts et al., 2021), and an additional increase of 20-25 million undernourished children in 2050 due to climate change (Phalkey et al., 2015; The Pontifical Academy of Sciences, 2017).

Apart from undernourishment, climate and extreme weather affects other components of hunger scores including stunting and wasting (von Grebmer et al., 2019), and all the four dimensions of food security (Wheeler & Von Braun, 2013). Worldwide, 144 million and 47 million children are stunted and wasted respectively, while micronutrient deficiencies are experienced by 2 billion people (Intergovernmental Panel on Climate Change, 2022). The different forms of malnutrition increase the risk of diseases and mortality, especially in children. For instance, it's estimated that almost half of all deaths occurring in under five children are attributable to child undernutrition[2] (Intergovernmental Panel on Climate Change, 2022). Future projections indicate that moderate and severe stunting among under-five will increase by an additional 570,000 cases to 1 million cases in 2030 under low climate (RCP2.6) and high climate scenarios respectively (RCP8.5) for 44 countries studied (Intergovernmental Panel on Climate Change, 2022), implying increased child mortality. Moreover, malnutrition, heat stress and other infectious diseases such as diarrhoea and malaria associated with climate events are projected to cause an additional 250,000 deaths between 2030-2050, reversing progress made in global health, undernutrition, attainment of universal health coverage and other development outcomes (World Health Organization, 2021), especially in developing countries. It's estimated that at least a half of the abovementioned additional deaths will occur in Africa with substantial contributions from child undernutrition, malaria and diarrhoea (Intergovernmental Panel on Climate Change, 2022).

In 2019, 2020 and 2021, the world was not only grappling with adverse impacts of weather-related natural hazards but also with COVID-19 pandemic, which aggravated effects from climate risks.

[2] In this dissertation: Undernutrition, a form of malnutrition, refers to measures of stunting wasting and underweight as used by WHO https://www.who.int/news-room/fact-sheets/detail/malnutrition. The 3 sub-forms of undernutrition are treated as health outcomes. Malnutrition is broader and includes undernutrition, overnutrition, inadequate minerals or vitamins and the resulting diet-related noncommunicable diseases.

Evidence exists that environmental factors such as temperature and seasonality driven by climate change facilitated COVID-19 transmission (Intergovernmental Panel on Climate Change, 2022). The pandemic caused remarkable harmful effects on human health and health systems (Marten et al., 2021) as well as on food systems, especially among the poor (von Braun et al., 2020). For instance, the pandemic increased the number of people facing acute food insecurity to 270 million globally and worsened malnutrition levels by about 1.5 to 9.9 percentage points in 2020 (Intergovernmental Panel on Climate Change, 2022). Furthermore, there was an increase in extreme poverty in 2020 by nearly 100 million people (Intergovernmental Panel on Climate Change, 2022). Although there exist similarities and interlinkages between these two global problems; COVID-19 and climate crisis, the latter may have considerably greater effects given that it develops slowly (Manzanedo & Manning, 2020), extends across generations and difficult to tackle (Klenert et al., 2020) while the former is direct and immediate (Howarth et al., 2020). However, the lessons learnt from handling the COVID-19 crisis can offer insights on how to better manage the climate crisis for a better future. For instance, some of the containment measures reduced greenhouse gas emissions (Intergovernmental Panel on Climate Change, 2022).

As evidence of the negative effect of climate events on health unfolds, adaptation and protective measures to increase human health resilience have been identified as an 'urgent research priority' globally for health policy (Marten et al., 2021; Whitmee et al., 2015; World Health Organization, 2009a), and to a greater extent in middle and low income countries. Indeed, the health sector was among the top three areas identified for adaptation in the Paris Agreement Nationally Determined Contributions - NDCs (Watts et al., 2019). Furthermore, adaptation measures for food systems and nutrition security, especially those related to agriculture, livestock and fisheries sectors remain the top most priority in the NDCs (United Nations Framework Convention on Climate Change, 2021). The above measures are categorized as health-related adaptation given that food is a major determinant of health. Furthermore, other integrated adaptation options that incorporate health into social protection, livelihoods, water and sanitation and infrastructure are also beneficial to health (Intergovernmental Panel on Climate Change, 2022). Overtime, there has been an increase in spending on adaptation to climate change within the health sector, an estimated 12.7% increase in 2018/2019 compared to 2017/2018, and an additional 7·2% increase in health-related adaptations (Watts et al., 2021). This indicates substantial progress in addressing the negative impacts of climate on human health, even though there exist stark differences in spending across continents, with Africa spending the least in terms of both health and health-related adaptation. Nonetheless, the recent climate change report still acknowledges existence of a substantial health adaptation deficit given the disastrous effects of climate on health (Intergovernmental Panel on Climate Change, 2022).

## Climate-health linkages

The relationship between climatic factors and human health is complex, and depend on many other factors that determine health vulnerability level to climate (World Health Organization, 2009a). Climate and extreme weather events may increase prevalence of diseases and undernutrition, cause injuries and loss of lives thus increasing health costs as well as work days lost and reduced labour productivity (Hutton, 2011; Kjellstrom et al., 2009), consequently affecting household consumption.

There exist several ways through which climate or weather events affect human health. The most common way is through intensifying the already existing health conditions or extending the range of already existing diseases into areas that were historically unaffected (Smith et al., 2014). In some instances, climate events may also cause new health conditions. These health effects occur through direct and indirect pathways. Direct health effects include injuries and mortalities occurring from extreme weather extremes such as floods, droughts and heat events (Filippelli et al., 2020; Smith et al., 2014; Watts et al., 2018). In addition, climate may directly influence growth and transmission of pathogens responsible for food and waterborne infections (Smith et al., 2014; World Health Organization, 2014).

Other infectious diseases including vector-borne diseases occur through the indirect pathways, mediated via natural systems, where changes in weather factors especially temperature alter the suitability, distribution and abundance of disease-causing vectors or pathogens (Smith et al., 2014). Indirect health effects such as undernutrition are mediated either through socio-economic factors such as food insecurity/inadequate food intake or through illnesses, especially infectious diseases (Phalkey & Louis, 2016; Smith et al., 2014). Extreme weather events such as floods may damage health infrastructure leading to losses of essential human drugs (Few et al., 2004; United Nations Children's Fund, 2021), inhibiting maternal and reproductive health services (van Daalen et al., 2020), food supplies (United Nations Children's Fund, 2021) and access to clean water (Neumayer & Plümper, 2007). Additionally, climate related natural disasters may affect people's livelihood through loss of assets and income leading to migration, fears, anxiety and other mental health issues (Few et al., 2004; World Health Organization, 2014). Taken as a whole, most of the health effects observed are indirect occurring when climate affects the key determinants of human health such as food, air, water and disease causing vectors (World Health Organization, 2009a). Whether direct or indirect, its documented that climate affects every category of human health including mental illness, non-communicable diseases and respiratory diseases (Liu and Gao, 2020; Watts et al., 2018; IPCC, 2022).

Among the mentioned health outcomes, undernutrition is one of the most detrimental health effects of climate in low- and middle-income countries. The number of stunted children in Africa is rising, despite the worldwide reduction in stunting. For instance, the number of stunted children in Africa increased to 61.4 million in 2020 as compared to 54 million in 2000 (United Nations Children's Fund et al., 2021). One of the possible reasons for the increasing number of stunted children in rural Africa is over-dependence on rainfed agriculture, which is sensitive to climate extremes, (Codjoe et al., 2011; Radeny et al., 2019; Yobom, 2020). Increased temperatures and extreme weather events may affect crop and livestock production leading to increased food and nutritional insecurity (Watts et al., 2018). Substantial literature reveals the sensitivity and negative effects of rainfall and temperature extremes on crop production (Hatfield & Prueger, 2015; Hu & Li, 2019;

Wheeler & Von Braun, 2013) , supply and consumption of macronutrients and micronutrients, especially zinc and iron which are of public health concern in developing countries (Nelson et al., 2018; Singh et al., 2012; Smith & Myers, 2018).

Apart from inadequate supply of food nutrients, undernutrition is also caused by infectious diseases such as diarrhoea (Humphrey, 2009) and malaria (Kateera et al., 2015). These diseases are mainly as a result of lack of sufficient quantities of good quality water for good hygiene, sanitation and drinking, lack of safety nets and inadequate health care (Hanna & Oliva, 2016), which are among major challenges in developing countries. In sub-Saharan Africa (SSA), an estimated 400 million people still have limited access to basic drinking water (Mason et al., 2019).

Vulnerability to the above-mentioned health effects are not equal across gender and age groups. Under five children are particularly vulnerable as they are susceptible to undernutrition and infectious diseases (Burke & Lobell, 2010; Smith et al., 2014; Watts et al., 2019). In addition, they have under-developed metabolism and physiology (Ahdoot & Pacheco, 2015), and total dependent on caregivers. Women are also more vulnerable to the health impacts of climate as compared to men mainly because of limited access to resources (Neumayer & Plümper, 2007) as well as due to differences in risk exposures and sensitivity. Literature documents that extreme weather events are likely to narrow women life expectancy, especially among women with low socio-economic status (Neumayer & Plümper, 2007; World Health Organization, 2014). Moreover, the recent IPCC (2022) report now recognizes gender differentiated implications of climate on health beyond pregnant women where women overall health is disproportionally affected. Gender dimensions of climate on health were neglected in the previous IPCC reports.

The pathways through which weather and climate affects health of different group of people are not the same. Therefore, this dissertation analyses the pathways through which extreme weather events affects under five children, men and women of the working age as well as the resulting effects of both weather and health shocks on overall household consumption outcomes.

## 1.2 Research problem and contribution of the study

Despite the highlighted health implications of climate and extreme weather events and the recent growing knowledge on the pathways, less has been studied especially in low income countries (LICs). Research gaps highlighted by the fifth IPCC synthesis report on human health include health effects of climate in LICs and health implications of different adaptation measures (Smith et al., 2014). Therefore, this dissertation aims to fill these gaps in literature, with a special focus on the most vulnerable individuals in rural agriculture-dependent households. Some of the challenges addressed throughout the chapter are connected to five sustainable development goals (SDGs) including zero hunger, good health and wellbeing, gender equality, clean water and sanitation and climate action.

First, the study unpacks the causal mechanisms between extreme weather events and undernutrition in children aged less than five years. Undernutrition is widely recognized as a risk factor to child mortality, diseases and may have severe consequences on children's physical and cognitive development, hence affecting future human capital and economic productivity (Headey et al., 2018; Phalkey et al., 2015). Globally, crop production is a major determinant of nutrient availability and it is estimated that 68% of zinc, 81% of iron, and 63% of proteins in human diets are derived from vegetable sources (Smith & Myers, 2018). For rural households in SSA, plants play an important role in the supply of essential mineral nutrients (Gibson, 2006; Yang et al., 2013). Furthermore livestock products play a key role in children's nutrition in early life, especially in the first 1,000 days (Alonso et al., 2019). Crop and livestock products are also a source of income to rural households which enable purchase of nutrient rich foods. However, both crop and livestock are sensitive to weather shocks and adversely affected by extreme weather events, resulting in poor health outcomes.

Even though there is substantial literature on the effects of weather and climate change on crop production (Anyamba et al., 2014; Haile et al., 2017; Lesk et al., 2016; McCarthy et al., 2021; Sultan et al., 2019), and effects of climatic factors on undernutrition outcomes such as stunting, wasting and underweight (Bahru et al., 2019; Cooper et al., 2019; Dercon & Porter, 2014; Grace et al., 2012; Hagos et al., 2014; Hoddinott & Kinsey, 2001; Muttarak & Dimitrova, 2019; Omiat & Shively, 2020; Rabassa et al., 2014; Shively, 2017; Tiwari et al., 2017). Most of these studies have been studied separately. A few studies examined some mechanisms through which weather shocks affect health (Hirvonen et al., 2020; Hoddinott & Kinsey, 2001; Hu & Li, 2019; Omiat & Shively, 2020; Shively, 2017). However, none of the abovementioned studies examined the nutrient supply pathways and simultaneously analysed a wide range of multiple channels that facilitate extreme weather events and undernutrition linkages. As earlier highlighted, undernutrition is an indirect health outcome of climate or extreme weather events, therefore studying causal mechanisms is more informative and of policy relevance as opposed to establishing the total effect and direct linkages between extreme weather and undernutrition. Furthermore, highlighting adaptation strategies that households use to minimize the negative health effects of weather extremes is important for policy and in addressing the nexus between weather events and health.

This study focuses not only on crop production but also on other pathways that have neglected in the past such as availability of macro and micronutrients supplied by food crops, market participation and livestock holdings. Micronutrients such as zinc and vitamin A are ranked among top ten risk factors for illness (Singh et al., 2012) and considered of particular public health concern in developing countries (Gibson, 2006; Nelson et al., 2018; Singh et al., 2012). These micronutrients are important for child growth and development and deficiencies have been associated with stunting (Fischer et al., 2019; Gibson, 2006; Rivera et al., 2003), and reduced child immune system (Kimenju & Qaim, 2016). Pathways related to disease environment, driven by access to portable and clean water and sanitation such as malaria and diarrhoea are also explored because diarrhoea inhibits intake of food and absorption of micro-nutrients (Muller & Krawinkel, 2005; von Braun, 2020a), and nutrients loss.

Extreme weather events will first affect these intermediate outcomes which represent inputs into child health production, and the respective weather-affected child health inputs will in turn affect child health, proxied by the different undernutrition measures. Since relationships between variables that results to undernutrition are usually complex, with much more pathways and linkages (Phalkey et al., 2015; Smith & Haddad, 2015) at both macro and microlevels (Smith & Haddad, 2015), extensive assessment of pathways that lead to undernutrition using individual and household level variables and robust methodologies on a national representative data is necessary.

The second research gap relates to the gender differentiated health effects of weather variability. More importantly is the quantification of the indirect effect of weather variability on health, through the water access pathway, and health inequalities to be eliminated if endowments were equalized among men and women. As "*a gender-based health inequality risk-multiplier*" (Sorensen et al., 2018; van Daalen et al., 2020; World Health Organization, 2014), weather variability and climate change may directly or indirectly affect health of men and women. Weather variability partly determines access to basic drinking water - one of the major challenges in developing countries with severe health consequences, and is gendered. Consensus exists that gender roles in particular contribute to health disparities between men and women (Ballantyne, 1999; King et al., 2018; Macintyre et al., 1996), and may constitute the indirect pathway through which climate affects health (van Daalen et al., 2020). Climate events may increase distance to water collection points or time spent on water collection activities beyond the recommended 30 minutes for round trip by WHO/UNICEF Joint monitoring program (JMP) for basic water access (World Health Organization & United Nations Children's Fund, 2017). As a result, there is reduced water consumption per capita, and increase in associated health effects, especially among women because of their increased water demands (World Health Organization, 2014) as well as exposure to increased heat (Sorensen et al., 2018), risk of violence (Graham et al., 2016; Sommer et al., 2015), and risk of musculo-skeletal illness during water collection activities.

Despite the existence of gender differentiated health of weather variability as highlighted by WHO framework, and possibility of worsening with climate change in future, there exist inadequate empirical evidence especially in developing countries, where substantial gender inequalities still exist. Currently, gender is underrepresented in climate and health research with very few articles integrating climate, health and gender in their studies, even in developed countries where relationship between climate and health has been largely studied (Preet et al. 2010). Furthermore, most of the studies are qualitative or descriptive in nature, with very few individual or household controls, and some focused on specific locations rather than the whole country. In view of this, the dissertation links climate, water, and health literature with a gender perspective and adds this component on the existing body of knowledge. Furthermore, the study decomposes the gender health gap in order to explain the source of the observed health differences among men and women, with special focus on weather variables and other determinants of health both at the extensive and intensive margin of illness for policy implications. The focus is on the working-age men and women, because this is an economically active age group and where gender aspects are more dominant.

The third research gap and contribution relate to the effects of both extreme weather events and illness on household consumption, and the different risk institutions used to insure consumption against illness. Despite the existence of fairly large body of literature on effects of weather on consumption (Alem & Colmer, 2021; Amare et al., 2018; Gao & Mills, 2018; Letta et al., 2018), and the effects of health shocks on consumption (Asfaw & von Braun, 2004; Gertler & Gruber, 2002; Hangoma et al., 2018; Islam & Maitra, 2012; Wagstaff, 2007), the two shocks have been studied separately using low frequency data.

This dissertation contributes to the above literature by focusing on both the effect of weather and health shocks, as well as the interaction of both shocks on household consumption. We combine the two shocks because they are the most important covariate and idiosyncratic shocks experienced by rural farming households in developing countries, and sometimes they co-exist. An additional contribution relates to the use of a very innovative intra-annual & intra-seasonal high frequency panel collected after every two to three months, with a total of six waves of data over a one-year period. This is consistent with Skoufias and Quisumbing (2005) recommendation of at least four waves of income and consumption data for studies on consumption insurance. Seasonal variations in rural agricultural households matter for food supply, employment as well as for spread of diseases. Given that climate events are key drivers of adverse seasonality, aggravating both consumption and incidence of illness (Chambers, 2013), high frequency data is most preferred in estimating the short-run connections and establishing the precise estimates of the effect of weather/health shocks on consumption. Furthermore, the dataset offers higher flexibility to account for possible omitted variables through fixed effects and has small inconsistencies as compared to low frequency data (Ghanem & Smith, 2021).

## 1.3 Main research questions

The main research questions listed below are examined in this dissertation. Under each of the research questions, adaptation or coping strategies employed by households to minimize the negative effects of weather events and health shocks are explored in the respective dissertation chapters.

1) What are the causal pathways through which extreme weather events affect children health outcomes?
2) What is the effect of weather variability on health outcomes of men and women in the working age group? Is the association between weather variability and illness mediated by water collection time?
3) What is the effect of extreme weather, illness and weather-induced illness on household total consumption, food and non-food consumption?

## 1.4 Study area in the broader context

Uganda is selected for this study, because it is highly dependent on rainfed agriculture, vulnerable to weather anomalies and infectious diseases, and prone to food and nutritional insecurities (Food and Agriculture Organization of the United Nations, 2020b; The Government of Uganda, 2018). Despite being a food sufficient country, food access and food utilization are still major problems, especially in the North, East and West Nile regions (Food and Agriculture Organization of the United Nations, 2020b; World Food programme, 2021). In addition, micronutrient deficiencies particularly iron, vitamin A and zinc poses a major health problem especially among children and women (FANTA, 2010). Globally, the country was ranked in position 104 out of the total 119 countries in 2019 on the hunger index[3] , with a score of 30.6, classified as serious hunger (von Grebmer et al., 2019). Even though this score signifies a reduction in hunger as compared to 2000 values (a hunger score of 38.9), mostly attributed to reductions in stunting, wasting and child mortality, the percentage of people undernourished has risen overtime (von Grebmer et al., 2019). Furthermore, hunger situation worsened in 2019 as compared to 2016 where the country was ranked in position 87 with the hunger index score of 26 (von Grebmer et al., 2019; von Grebmer et al., 2016). Approximately 41% of population were undernourished for the period 2016-2018 (Food and Agriculture Organization of the United Nations et al., 2018; von Grebmer et al., 2019), prevalence of stunting rates and wasting was 29% and 4% between 2014-2018 while under five child mortality rates were estimated at 5% in 2017 (von Grebmer et al., 2019).

Malnutrition is recognized as the underlying cause of about 60% and 25% of infant and maternal deaths respectively (Ministry of Health, 2015), and contributory risk factor to both premature death and disability in the country (Food and Agriculture Organization of the United Nations, 2020b; Institute for Health Metrics and Evaluation, 2019b). It is estimated that 250,000 deaths of young children that occurred from 2013 to 2015 in Uganda were attributed to undernutrition (United Nations Children's Fund, 2015a). Therefore, malnutrition is a key challenge to achievement of sustainable development. In terms of overall progress towards meeting the SDGs, Uganda was ranked in position 142 out of 166 countries in 2020 (Sachs et al., 2021).

Despite being among the poorest countries in the World, Uganda has recorded a tremendous achievement in poverty reduction overtime. For instance, the national poverty head count ratio based on national poverty line (US$0.88–US$1.04) reduced from 56.4% in 1993 to 19.7% in 2013 and 21.4 % in 2016. However, the number of people not poor but vulnerable to fall below the poverty line has increased overtime and was 43.3% in 2013 (Development Initiative, 2020). To date, Eastern and Northern parts remain the poorest regions in Uganda (Development Initiative, 2020). The location of Uganda on Africa map and different regions in the country are shown in Figure 1.2.

[3] Three of the four indicators used to construct the hunger index score are related to child nutrition and health (child stunting, child wasting, and child mortality) and undernourishment.

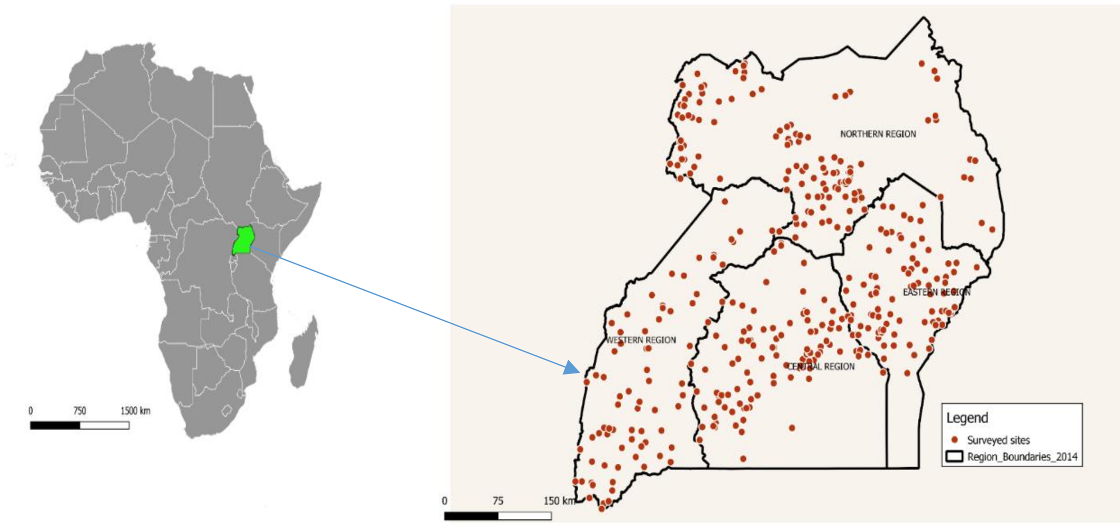


**Figure 1.2**: The location of Uganda in Africa and World Banks survey sampled sites

### 1.4.1 Extreme weather events, annual and monthly weather trends, and seasons

Growing impacts of droughts and other climatic hazards such as floods, heat waves, landslides and associated diseases and pests are becoming evident (The Government of Uganda, 2018; The World Bank & Global Facility for Disaster Reduction and Recovery, 2019). Devereux and Nzabamwita (2018), and Uganda Bureau of Statistics (2019) reported that drought events that occurred between 2015 - 2017 were partly responsible for increasing poverty rate from 19.7% in 2013 and 21.4 % in 2016.

Uganda was ranked as the 14$^{th}$ most affected country globally by extreme weather events in terms of economic losses and fatalities in 2018, with an overall score of 24.7 (Eckstein et al., 2019). Between 1999–2018 the country was ranked in position 62 with an overall climate risk index score of 69.33 (Eckstein et al., 2019). These figures imply that vulnerability and level of exposure of the country to extreme weather events has increased over the years, with harmful effects on food security, economy and human health. Each year, approximately 200,000 and 500,000 people are affected by drought and flood events, respectively, and at least 7% of the farming households are prone to flooding (The Government of Uganda, 2018; The World Bank & Global Facility for Disaster Reduction and Recovery, 2019). These extreme events are most often experienced in poverty stricken areas along the cattle corridor stretching from mid Northern, Eastern, Central and South-western Uganda (The Government of Uganda, 2018; The World Bank & Global Facility for Disaster Reduction and Recovery, 2019). Flooding and landslides due to extreme rainfall are mainly experienced in Eastern Uganda as well as some districts in the Western part of the country and flash floods in the North. In summary, it's estimated that 20 floods, 5 landslides, 9 droughts and 40 epidemics occurred in the country for the period between 1900-2018 (World Bank Group, nd).

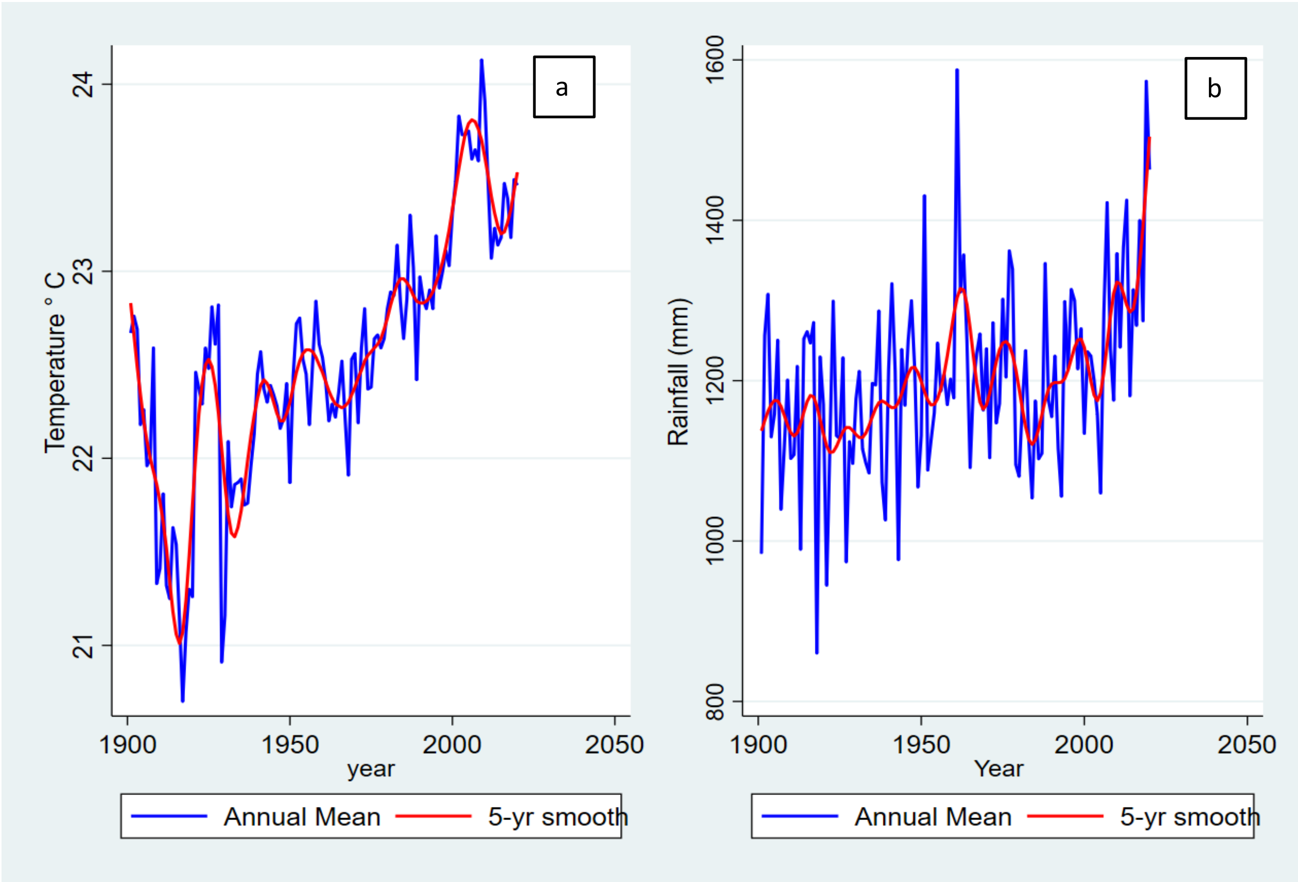


**Figure 1.3**: Annual temperature and rainfall trends in Uganda from 1901 to 2020 (a &b)
Source: adapted from the World Bank data (1901-2020)

The country experiences an average annual rainfall of 1200mm ranging from 500mm-2800mm in some areas and monthly temperature range of 15-30$^0$C with an annual mean of 22.5$^0$C (World Bank Group, nd). Overtime, there has been fluctuations in rainfall amounts as shown in Figure 1.3. However, the five-year smoothed averages indicate an increase in rainfall in the recent years. The rainfall amounts received in the country are relatively higher compared with the neighbouring countries in East Africa (Tanzania and Kenya) (Ssentongo et al., 2018), even though the country's economic growth rate is relatively lower compared with other East African countries. Figure 1.3 (a) indicates fluctuations in historical annual average temperature from 1901 to 2020. However, a steady increase is observed since 2000.

Uganda climate is heterogeneous with considerable regional differences. The driest and hottest districts are located in Karamoja which is among the poorest areas in the world (United Nations Population Fund, 2018). The districts with the lowest rainfall include Kotido and Moroto receiving historical annual mean rainfall (1980-2009) of about 702mm and 856mm respectively and average temperature of 32$^o$C (Egeru et al., 2019).

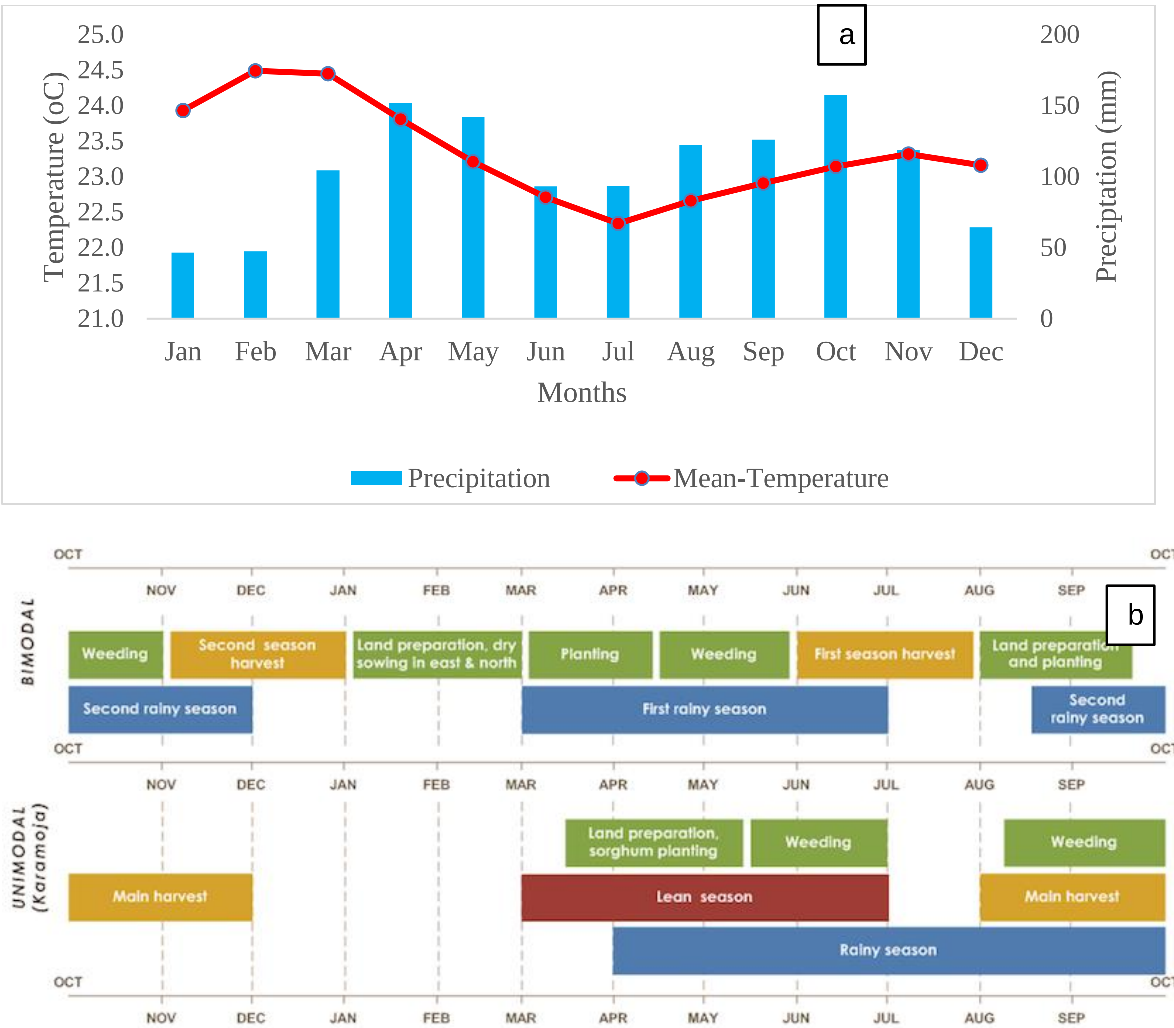


**Figure 1.4**: Monthly rain and temperature for Uganda, 1991-2020 (a) and season calendar (b)
Source: Figure(a) author elaborations, adapted from the World Bank data. Figure 1.4 (b), adapted from FEWSNET (2021)

Concerning temperature variability, Caffrey et al. (2013) reported a significant temperature increase of about 0.5-1.2°C experienced for time periods 1981-2010 and 1951-1980 while Funk et al. (2012) reported an increase in temperature of up to 1.5°C. Information on the average monthly rainfall and temperature of Uganda for 1991-2020 is detailed in Figure 1.4 (a) where temperatures were highest in February and March and lowest in June, July, August and September. Rainfall amounts were highest in April, May, August, September and October.

Annual mean temperatures are projected to increase with an average of 2.5°C to 4.4°C and 4.5° to 6.0°C in some areas in the near future (2021-2050) and in mid-century respectively relative to 1981-2010 average under IPCC Special Report on Emission Scenarios (SRES) A2 (Nimusiima et al., 2014). These figures are consistent to those reported by Maggio et al. (2021), annual temperatures increase of 3.2°C in some areas in the near future until 2050 as compared to 1960. It is projected that the change in monthly temperature will be highest in the historical cold months (May-July) with an increase of upto 4 $^{o}$C (World bank n.d). While most of the temperature projections are consistent indicating an increase in near surface temperature, future rainfall trends are not clear. For instance, Nsubuga and Rautenbach (2018) reports an expected decrease in precipitation in most parts of the country while Nimusiima et al. (2014) forecast wetter conditions as a result of increase in rainfall especially in second season rains and the previously dry months from December to February.

Generally, the annual agricultural cycle is bimodal in most regions of the country, except the North-eastern region which experiences unimodal type of rainfall. The first season (long rains) occurs between March – May while the second season (short rain) occurs in September -November (Ssentongo et al., 2018). Karamoja receives one long rainy season running from April to November, sometimes with a break in June (U.S. Agency for International Development, 2017), as shown on the seasonal calendar in Figure 1.4b.

There has been a substantial reduction in rainfall amounts of about 6mm per month for the first season, specifically in the months of March, April and May, per decade (World Bank n.d). A larger magnitude of interannual variability is experienced in the short rains season as compared to the long rains season (Kisembe et al., 2019). Notably, since 2018, extreme rainfall and flooding events, linked to a positive Indian Ocean Dipole (IOD) have been recorded in the second season through December. According to Uganda National Meteorological Authority (2021), most parts of the country received above normal rainfall in the second season with September and November receiving much wetter rainfall than usual. Above than normal rainfall has mixed effects on crop production given that it is sometimes accompanied by locust infestation. In 2020, a desert locust outbreak occurred in February affecting the Karamoja, Lango and Acholi subregions (Food and Agriculture Organization of the United Nations, 2021b). Furthermore, extreme rainfall is unfavourable for legumes and pulse crops and most crops especially in the mountainous regions, and further inhibits proper drying leading to increased post-harvest losses (Famine Early Warning System Network, 2020). Increased rainfall has facilitated infectious disease outbreaks in the country (Ssentongo et al., 2018), and Malaria is one of the diseases linked to warm temperatures and flooding.

### 1.4.2 Structure of Uganda’s rural economy and agriculture

Uganda is predominantly a rural society with more than 80 per cent its population living in rural areas (Deutsche Gesellschaft für Internationale Zusammenarbeit, n.d; Mukwaya et al., 2011). Majority of the poor people in Uganda live in rural areas as opposed to urban areas (Mukwaya et al., 2011). For instance, it’s estimated that approximately 95 percent of the poor people live in the rural areas (Deutsche Gesellschaft für Internationale Zusammenarbeit, n.d). Majority of the rural residents depend on agriculture as their main source of food, income and overall livelihood. Thus the sector is recognized as the major route out of poverty for most Ugandans (Mukwaya et al., 2011; U.S. Agency for International Development, 2021). Indeed, the outstanding achievement in reduction of poverty in Uganda recorded over the past decades was to a larger extent driven by agriculture sector (U.S. Agency for International Development, 2021).

Generally, the agricultural sector is important for Ugandan economic development since it accounted for 25 per cent of Gross Domestic Product in 2014 (Deutsche Gesellschaft für Internationale Zusammenarbeit, n.d). Approximately, 79 percent of households are engaged in farming and the sector provides employment and income to about 70 percent of the working population in the country (Mukwaya et al., 2011), 72 percent of all youths and 64 percent of all Ugandan population respectively (Republic of Uganda, 2022). The agricultural sector is also important for Uganda's international trade given that agricultural products accounts for nearly half of all country's exports total value (Mukwaya et al., 2011; Republic of Uganda, 2022; U.S. Agency for International Development, 2021). The main export crops in the country are coffee, tobacco, tea, cotton, cocoa, beans and sugar (Muggaga et al., 2022; Mukwaya et al., 2011). The Uganda agricultural sector is also important source of food to the neighbouring countries and regional market, especially Kenya where Uganda regularly supplies beans and Maize (Mukwaya et al., 2011). Therefore, agricultural productivity is key in accelerating and sustaining growth in the country (U.S. Agency for International Development, 2021). Compared with other sectors, the Agriculture sector demonstrated significant growth in the past four years where the sector grew by 4.2 percent up from 3.8 percent while services and industry grew by 3.6 percent and 2.3 percent over the past four year (Republic of Uganda, 2022).

While a few agricultural products make up majority of the country's exports, agricultural production in the country is mostly subsistence oriented rather than commercial (Mukwaya et al., 2011). In most regions, agriculture production is mainly characterized by smallholder farming who use fewer modern inputs, basic tools, and depend largely on family labor supply. Most farmers have diversified production even though it's for local or own consumption and not largely for trade (Mukwaya et al., 2011). This implies that most Ugandans enjoy a diversified food diet. For those who sell, they mostly market their agricultural produce immediately after the harvest in order to meet other household need such as school fees and later go back to the market to purchase same products at a relatively higher price once their produced stock is depleted (Mukwaya et al., 2011).

Food crops produced by smallholder farmers and regarded as staples include: maize, cooking bananas, sorghum, millet, sweet potato, cassava, Irish potato and rice (Muggaga et al., 2022). Other crops include a variety of fruits, vegetables and pulses (Muggaga et al., 2022; Mukwaya et al., 2011). Crop yields for all of the above mentioned commodities are generally low and the yield gap between mean farm yields and yields from research farms imply that there is the tremendous potential for crop productivity improvement (Mukwaya et al., 2011). Over the past years most increases in crop production has been as a result of expansion of cropped area as opposed to improved yields on cropped land (Mukwaya et al., 2011). The average size of land holding for an agricultural household was 0.9 hectares by 2005, and is likely to have reduced overtime due to population increase increasing land pressure (Mukwaya et al., 2011). Furthermore, the land tenure system is mostly customary limiting long-term investment and sustainable higher crop productivity. Other challenges contributing to poor agricultural performance and slowing down the country transition from subsistence to surplus production for market sales include lack of knowledge and limited use of improved farming methods and inputs such as organic or inorganic fertilizers, improved seed and use of pesticides which are exacerbated by high input costs and low crop output prices (Mukwaya et al., 2011). Processing and value addition to agricultural products is also low by regional standards, and there is high post -harvest losses and low quality of produce (Deutsche Gesellschaft für Internationale Zusammenarbeit, n.d).

Apart from crop production, Ugandans also depend on livestock, aquaculture and apiculture which are gaining prominence (Muggaga et al., 2022). Most households practice mixed farming , rearing unimproved cattle, poultry, goats (Mukwaya et al., 2011), sheep and pigs (Muggaga et al., 2022). Large herds of unimproved cattle are mostly common in the Northern region which is predominantly pastoralists. Across different regions in the country, there has been an increase in production of livestock due to substantial efforts taken to improve production systems, control of livestock diseases and steady livestock extension support (Muggaga et al., 2022).

### 1.4.3 Socio-demographics and gender

The country's annual population growth rate is one of the highest in the world estimated at 3% per annum (Kilama Luwa et al., 2020). This high annual population growth rate poses a huge challenge for economic development in the country (Mukwaya et al., 2011). According to the World Bank data, approximately 50.7% of the total population of Uganda (44 million) in 2019 were female. The country is currently experiencing demographic transition with approximately 51.5% (22.8M) of its population in the working age category (15-64 years) as of 2019 (World Bank, n.d) with increased projections of 60.9% (113.8M) by 2080 (Economic Policy Research Institute et al., 2019). The working age category was dominated by the female 11.7M (52% of female population) in the reference period. Additionally, a high proportion of female (2%) were in the old age category as compared to male (1.6% of the male population), while the proportion of boys aged between 0-14 years was higher at 47.6% as compared to 45% for female (World Bank, n.d). The total population aged 0-14 years and above 65 years was 20.6M and 0.9M accounting for 46.5% and 2% of the total population respectively (World Bank, n.d). The Age dependency ratio as a percentage of the working-age population was estimated at 94% (World Bank, n.d).

Just like other SSA country, gender inequalities in Uganda are still persistent with detrimental effects on development. Globally, Uganda was ranked position 65 out of 153 countries and position 10 in the SSA, with a score of 0.717 in progress towards achievement of gender parity (World Economic Forum, 2020). This score denotes significant progress as compared to 2016 where the gender gap index was at 0.680 (World Economic Forum, 2016). However, the country performed better in 2017 and 2018 where the gender gap indices were 0.721 and 0.724 respectively, and in positions 45/144 and 43/149 respectively (World Economic Forum, 2017, 2018). One of the major progress contributing to a better position and index in 2018 was progress made in health, in terms of life expectancy (World Economic Forum, 2018). In the recent ratings, Uganda outperformed its neighbouring countries, ranked in positions 68, 109 and 149 globally for Tanzania, Kenya, and Democratic republic of Congo respectively (World Economic Forum, 2020).

At national level, Uganda acknowledges gender as a crucial component in development work through its National Gender Policy. The policy addresses gender inequalities and guides its development practitioners towards this achievement (Uganda National Policy, 2007). Furthermore, the Policy highlights tremendous progress in addressing gender inequalities and women empowerment in all spheres of life, including health as well as challenges in the attainment of the gender equality. Apart from the gender policy, the Uganda health sector development plan (2015/2016 – 2019/2020) details the progress achieved in health and how health sector strategies and policies take gender into account as a determinant of health, and recognition that men and women are affected differently (Ministry of Health, 2015).

### 1.4.4 Health trends in Uganda

The country recorded substantial achievements on health indicators over the past years. These achievements include; reductions in fertility rates, low infant and under-five mortality rates which are attributed to advancements in education and provision of health care among other human development factors (Ministry of Health, 2015). For instance, education life expectancy of female students doubled to 10 years in 2014 as compared to 5 years in 1990, while the fertility rates reduced to 5.4 children in 2016 as compared to 6.9 in 1950 (Economic Policy Research Institute et al., 2019).

With regards to the general burden of the disease, despite notable improvements, the health sector development plan 2015/16 - 2019/20 indicates that the demographic and epidemiological transitions in Uganda presents a complex burden of communicable and non-communicable diseases, together with injuries, mental health and health issues related to violence (Ministry of Health, 2015). Even though the burden of non-communicable diseases is rising in the country – contributing to 11-13% of the total disease burden, infectious diseases still account for a higher proportion of the disease burden (Ministry of Health, 2015). However, mortalities from non-communicable diseases were estimated to be higher as compared to those of communicable diseases in 2018, more so in men (World Economic Forum, 2018). For instance, mortalities from communicable and non-communicable disease in males was estimated at 45.6 deaths per 100,000 and 51.9 deaths per 100,000, and 41.2 and 48.5 per 100,000 for female respectively (World Economic Forum, 2018).

Common diseases in Uganda include; neonatal disorders which contribute to 16.8% of the total DALYs. Malaria, HIV/AIDs, lower respiratory infections and diarrhoea are among the top 10 important diseases contributing to 11.19%, 7.52%, 5.27% and 4.26% of the DALYs (Institute for Health Metrics and Evaluation, 2019a). Other diseases contributing to most deaths in Uganda include meningitis, tuberculosis and measles among other emerging and re-emerging diseases and neglected tropical diseases (Ministry of Health, 2015). Gender based violence poses health risks to most Ugandan women and limits productivity (Rutakumwa & Krogman, 2007; Uganda Bureau of Statistics & Macro International Inc., 2007). The global gender gap report for 2017 and 2020 estimates that the prevalence of gender-based violence in lifetime for women in Uganda was approximately 50% on average (World Economic Forum, 2017, 2020), which is among the highest rate of violence in the world (Wodon & Onagoruwa, 2019; World Economic Forum, 2020).

### 1.4.5 Gender differences in health outcomes

In comparison to women, infant mortality rates, under-five mortality rates and adult mortality rates have historically been higher in male as shown in Figure 1.5. For instance, infant mortality rates in males were estimated at 36.9 per 1,000 live births in 2019 as compared to the average rate of 33.4 deaths, while under-five male mortality rates were estimated at 50.5 deaths per 1,000 as compared to the average of 45.8 and 41 deaths per 1,000 live births in female (World Bank, n.d). Adult mortality rates were also higher in males at 302.4 per 1,000 male adults aged 15-60 years while female mortality rates were at 233.27 in 2018 (World Bank, n.d). A reduction in maternal mortality rates was recorded in 2014 at 360 per 100, 000 as compared to 2011 where the rate was 438 per 100,000 (Ministry of Health, 2015).

The aforementioned factors have substantially contributed to increased life expectancy in the country for both men and women (Ministry of Health, 2015; Economic Policy Research Institute, 2019). Compared to 40 years of life expectancy in 1950, there was a substantial increase of over 20 years by 2018 where life expectancy at birth was estimated at 63 years, with female having higher life expectancy than men at 65.2 and 60.7 years respectively as shown in Figure 1.5 (World Bank, n.d)[4]. It is projected that mortality rates will continue to reduce in the future, thus increases in life expectancy. For instance, it is estimated that under five mortality rates will be 22 deaths per 1,000 live births while life expectancy is estimated at 76.5 years by 2080 (Economic Policy Research Institute et al., 2019).

[4] https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=UG

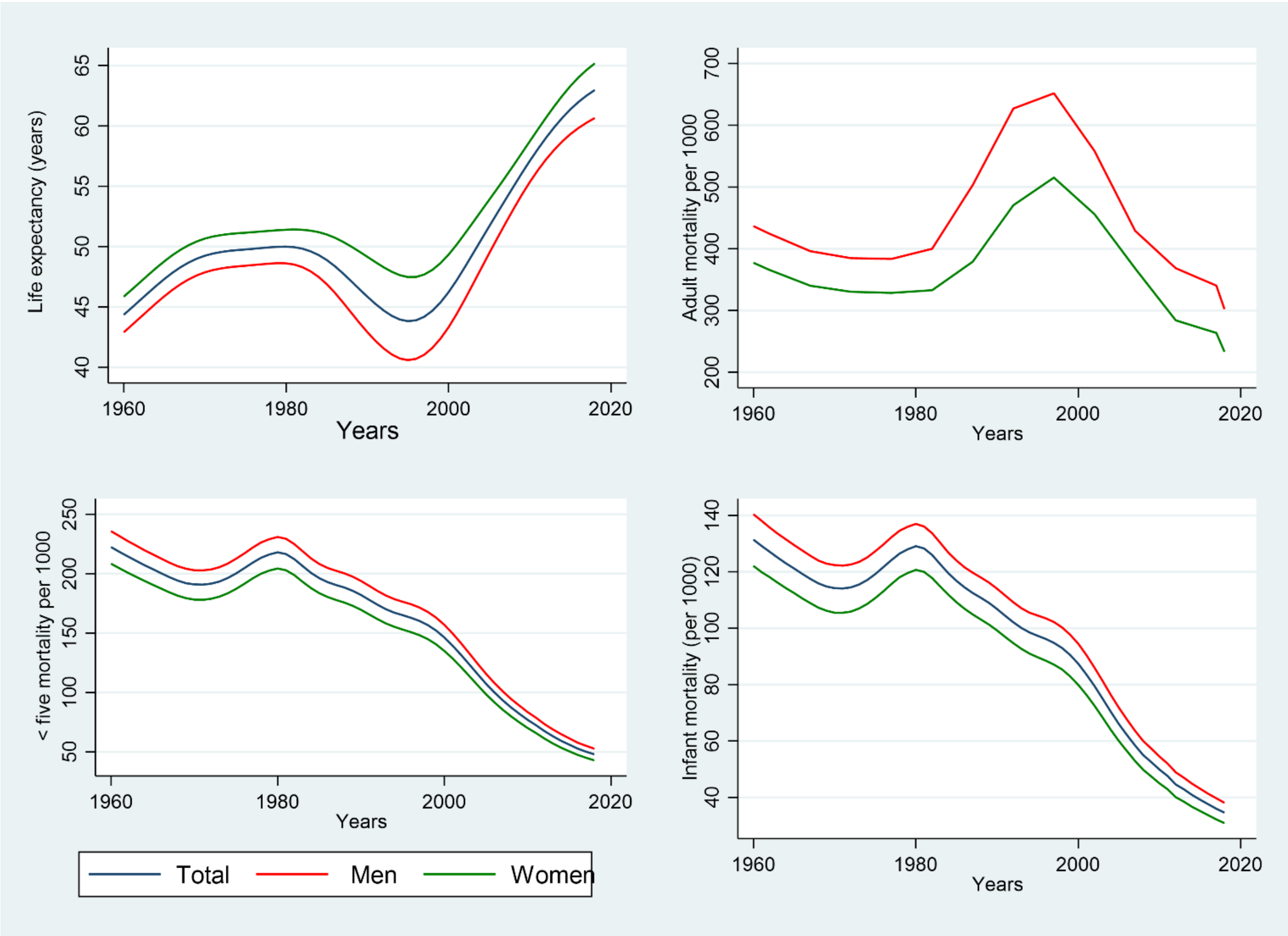


**Figure 1.5:** Life expectancy, infant and adult mortality rates in Uganda

Source, adapted from the World bank data

### Health financing

The government allocated only 6.4% of its national budget on average on the health sector for the time period 2015/16 – 2019/2020, which is below the Abuja target of about 15% (Initiative for Social and Economic Rights, 2018). According to health financing strategy 2015/16 -2014/25, 15.3% of the total health expenditures in 2011/2012 were financed by the government, development partners contributed 46.5% and 38.4% were financed through private funds from households out of pocket expenditures (Ministry of Health, 2016). Coverage of health insurance is lower, with private insurance covering only 1% of the population and concentrated in urban areas (Dowhaniuk, 2021). Community based health insurance schemes (CBHI) also exist mainly in the southern region of Uganda but majority of poor households are not enrolled because of CBHI premium fees (Dowhaniuk, 2021). In 2001, user fees were eliminated in government health facilities, however, there exist a dual system at hospital level with a wing allowing for payments for those who can afford (Orem & Zikusooka, 2010). The health systems in Uganda is decentralized and in march 2021 the parliament of Uganda passed the National Health Insurance Scheme Bill.

## 1.5 Organization of the thesis

This thesis consists of a total of five chapters. Chapter 1 details background information and research context, research problem and contributions of the study, main research questions and detailed information on the study area. Chapter 2 evaluates the causal pathways through which extreme weather events affects child health in terms of HAZ, WAZ and WHZ. This chapter assess the relationship between extreme weather events and the supply of macronutrients and micronutrients essential for child growth and development, and the corresponding effect on child health. Additionally, it explores other channels related to disease environment, livestock, market participation and infrastructure and a wide range of adaptation and coping strategies used by households. Chapter 3 examines the total and direct effect of weather variability on illness among men and women, and the extent to which water collection 'time burden' mediates the relationship between weather anomalies and illness (indirect effect). This chapter also decomposes the health gender gap in order to explain the sources of these differences based on covariates that largely contribute to the observed gap. Chapter 4 analyses the effect of weather, illness and weather induced illness on household consumption, possible transmission channels and identifies different risk sharing institutions used to smooth consumption. Furthermore, the chapter explores the relationship between food consumption and health. Chapter 5 concludes by summarizing key research findings, policy implications and limitations of the study.

# Chapter 2: Effect of extreme weather events on nutrition and child health

## 2.1 Introduction

The intensity and frequency of extreme weather events have increased globally over the recent years (National Research Council, 2020). It is estimated that 712 extreme weather events occurred in 2017 (Watts et al., 2018), and approximately 160 million and 500 million children were residing in areas experiencing high severity of drought and extreme floods in 2015, respectively (Ghani et al., 2017; United Nations Children's Fund, 2015). Future climate change projections indicate warmer years, and more extreme weather events (Watts et al., 2018; Yobom, 2020), potentially posing severe risks to human wellbeing and health (Filippelli et al., 2020; Sellers, 2020; Watts et al., 2019). For instance, the number of people living in water-stressed areas is projected to rise to 5 billion by year 2025 (Phalkey & Louis, 2016), while the number of undernourished children is projected to increase by 20-25 million due to climate change in 2050, comparing with and without climate change A2 scenarios (Phalkey et al., 2015; The Pontifical Academy of Sciences, 2017).

Extreme weather events and climate change impact the health of people through injuries, illness, deaths and undernutrition (Bell et al., 2018; Filippelli et al., 2020; Franzke & i Sentelles, 2020). Watts et al. (2019) indicate that children born today are likely to experience a warmer world (at least 4°C above the historical average), facing higher climate related health impacts in all stages of their lives. Compared to other age-groups, children are particularly vulnerable as they are susceptible to undernutrition and infectious diseases (Burke & Lobell, 2010; Smith et al., 2014; Watts et al., 2019), in addition to their under-developed metabolism and physiology (Ahdoot & Pacheco, 2015). In fact, Bhutta et al. (2019) estimate that nearly 88% of the disease burden arising from climate change and variability is borne by children.

Undernutrition in particular, is recognized as a major health impact due to climate change and variability (Cooper et al., 2019; Sellers, 2020). Besides, undernutrition is also a risk factor for other infectious diseases, respiratory diseases and child mortality (Hasegawa et al., 2016; Troeger et al., 2018) thus, creating "*undernutrition- infections vicious cycle"* (Maleta, 2006). Disease burden estimation of at least 50% of years lived with disability (YLD) in children under four years is attributed to nutritional deficiencies (Ebi & Bowen, 2016; Vos et al., 2012). These health effects have severe consequences on children's physical and cognitive development and hence future educational, economic productivity and income levels given that some of them are irreversible (Phalkey et al., 2015; World Health Organization, 2009b).

Worldwide, about 149 million and 45 million of under-five children were stunted and wasted in 2020 respectively (WorldHealthOrganization, 2021). The absolute number of stunted children in 2020 was approximately 31 million and 55 million less, as compared to 2010 and 2000 respectively. Despite the worldwide reduction in stunting, the number of stunted children in Africa is rising. For instance, the number of stunted children in Africa increased to 61.4 million in 2020 as compared to 54 million in 2000. Similarly, the global climate risk index report reveals that the poorest nations are the hardest hit by the climate events (Eckstein et al., 2019), which have increasingly contributed to high hunger levels and food insecurity (von Grebmer et al., 2019). Indeed, the recent empirical literature on climate and health has revealed that stunting is very sensitive to shocks related to climate and weather anomalies (Cooper et al., 2019). Additionally, Phalkey and Louis (2016) report a correlation between increasing number of droughts in SSA with the increasing stunting rates, despite worldwide reductions in undernutrition rates. As the likelihood of extreme weather events increases, progress towards "*a world with food security for all*" (von Braun, 2020b) is not only jeopardized, but also could reverse further the gains achieved globally in stunting reduction (Cooper et al., 2019), and worsen the situation in Africa. Unless adequate adaptation measures and safety nets are in place.

Understanding the linkages between extreme weather events and health is important. While there are direct health effects from weather extremes such as injuries and mortalities related to floods and heat events (Filippelli et al., 2020), most detrimental and life-long impacts on child health related to undernutrition are indirect, mediated either through socio-economic factors such as food insecurity/inadequate food intake or through illnesses such as infectious diseases (Phalkey & Louis, 2016; Smith et al., 2014). The above mentioned factors contribute to the largest burden of undernutrition, and are susceptible to weather changes and extreme weather events (Phalkey & Louis, 2016). Yet, empirical studies focusing on these interlinkages through a simultaneous approach, and further joint estimation of diverse health impacts are scanty (Phalkey and Louis 2016; Phalkey et al. 2015).

Against this background, this study contributes to previous literature by conducting simultaneous analysis on multiple agriculture related channels that are important to rural household's nutrition and health, and are sensitive to weather extremes. Importantly, we assess the relationship between extreme weather events and the supply of macronutrients and micronutrients essential for child growth and development. There exists limited empirical evidence on the effect of weather extremes on mineral composition of food crops, and the resulting effect of nutrients on child health. We also consider other channels related to disease environment because childhood diseases have an impact on both physical growth and cognitive development of children. Another key added value of this study is that it uses longitudinal data on children's anthropometric measures and focus on the three undernutrition measures. We also control for both temperature and precipitation extremes as well as a wide range of adaptation and coping strategies. This study therefore assesses the causal mechanisms through which extreme weather events affect children health outcomes in terms of HAZ, WAZ and WHZ. In addition, we examine strategies that households use to minimize the negative effects of weather extremes.

We find evidence of significant and negative effects of both temperature and precipitation extremes on both the quality and quantity of crop production, market sales and livestock. Furthermore, both droughts and heatwaves significantly increased the probability of diarrhoea. In the second stage, increases in nutrient production, especially zinc and protein significantly led to better HAZ, WAZ and WHZ while an increase in livestock holding had positive and significant effects on WAZ and WHZ. We fail to confirm consistent and significant impacts of crop sales and fever on child health. However, diarrhoea significantly led to poorer HAZ and WAZ. Child health is therefore affected by droughts and heatwaves through their effects on nutrients, crop production, livestock and diarrhoea. Coping and adaptation strategies such as precautionary savings, nonfarm work, access to credit, water harvesting, pesticides use, improved seed and crop diversification helped households smooth the negative effects of different weather extremes on both crop yield and child health. Furthermore, market access and good road network facilitated better crop outputs and child nutrients. These results were consistent and robust in a number of econometric specifications. We therefore advocate for the development and scaling up of interventions that protect child health from adverse effects of extreme weather events. The rest of the paper is organized as follows: section 2.2 outlines literature review, conceptual and theoretical frameworks, section 2.3 describes materials and methods, section 2.4 presents' results while relevant discussions, conclusions and limitations of the study are detailed in section 2.5.

## 2.2 Literature review, conceptual and theoretical frameworks

### Literature review

Empirical literature on the effect of climate or weather variability on child nutritional outcomes can be classified into three strands. The first strand of literature focuses on the vulnerability of child health to impacts of climate change and variability while still in the *utero*. The second is on impacts of weather extremes after the child is born and during her/his early life, while the third strand is on studies projecting the future impacts of climate change on future undernutrition rates. The first strand of literature claims that due to maternal bond during pregnancy, exposure of pregnant women to weather extremes and anomalies results in maternal undernutrition, food insecurities, respiratory illnesses, heat related diseases, stress and poverty that can consequently lead to high risk of pre-term birth and low birth weight of children (Pacheco, 2020). These negative effects on child development can be both short-term and long-term. For example, Hu and Li (2019) find that heat stress experienced during pregnancy had long-term negative effects on height of born individuals in their later life. Deschenes et al. (2009) report a negative relationship between extremely high temperatures and birth weight on a global sample of 37.1 million births. Other related studies document a decrease in birth weight due to maternal exposure to increases in temperature in Andean region (Molina & Saldarriaga, 2017), low birth weight attributable to high temperatures and low rainfall in 19 African countries (Grace et al., 2015) and lower WHZ under maternal drought exposure in India (Kumar et al., 2016).

Child stunting (low HAZ) is one form of undernutrition resulting from long-term nutritional changes. Some studies have linked precipitation extremes (droughts and floods or extreme wetness) with stunting and other forms of undernutrition, while considering different periods of early child life. Shively (2017) finds a positive relationship between HAZ and WHZ, and rainfall experienced during growing seasons of the birth year, preceding survey year and also while in the *utero*. Apart from the aforementioned study, a strand of literature has used Standardized Precipitation–Evapotranspiration Index (SPEI) to assess the relationship between precipitation extremes and stunting. Using data from 53 countries, Cooper et al. (2019) find that increase in child stunting (HAZ scores) was associated with precipitation extremes. Similarly, Muttarak and Dimitrova (2019) using SPEI find that floods or abnormally wet conditions increased probability of stunting and wasting of under five children in Kerala, India. In contrast, Nsabimana and Mensah (2020) reveal that wet shocks did not have distinct effects on child stunting in Tanzania. However, the latter study finds a positive and significant impact of dry shocks on stunting.

Bauer and Mburu (2017) and, Johnson and Brown (2014) use normalized difference vegetation index (NDVI) as a drought indicator in Kenya, and in four West Africa countries respectively. These two studies find mixed results on stunting and mid-upper arm circumference (MUAC). While Bauer and Mburu (2017) find a negative relationship between NDVI z-score and the probability of child malnourishment as measured by MUAC, Johnson and Brown (2014) report that NDVI for child's birth year was inconsistently associated with stunting, positively with wasting and negatively with the mortality risk. Other studies exploring the linkages between climate or weather variables and their proxies on undernutrition with mixed results are as follows; Grace et al. (2012) find a significant positive impact of rainfall on the HAZ scores of under five children in Kenya. Similarly, Rabassa et al. (2014) report positive association between positive rainfall shocks and HAZ scores as well as negative effects of high temperatures on HAZ in Nigeria. Contrary to the above studies, Hagos et al. (2014) reveal that increases in rainfall and temperature resulted into increase and decrease in moderate stunting, respectively.

A set of studies that find positive correlation or impact between drought and stunting or negative effect on the HAZ and height include; Bahru et al. (2019) reporting low HAZ scores on children in Ethiopia, Dercon and Porter (2014), where children who were below 3 years at the 1984 drought incidence peak had lower height- difference of 5cm as compared to older ones. Similarly, Amondo et al. (2021) report low HAZ due to drought in Uganda. Jankowska et al. (2012) find an association between stunting with water balance index in Mali while Hoddinott and Kinsey (2001) report a loss in growth of child height of about 1.5-2 cm in the drought aftermath in Zimbabwe. Conversely, Hirvonen et al. (2020) document that 2015 drought did not significantly lead to undernutrition (stunting or low HAZ), but poor road network interaction with drought was a mediating factor for undernutrition in 43 clusters of Ethiopia. Rodriguez-Llanes et al. (2016) focusing on flood argue that there was no correlation between flooding and stunting in Eastern India.

With regards to wasting and underweight or low weight measures, Rodriguez-Llanes et al. (2016) find significant association between flooding, wasting and underweight. Thiede and Strube (2020) report that low rainfall was associated with low child weight, while high temperatures led to low child weight as well as increasing the risk of wasting. Studies by Rabassa et al. (2014) and Tiwari et al. (2017) find positive impacts of above than normal rainfall on WHZ. However, Omiat and Shively (2020) report negative connections between high precipitation and child WHZ in Uganda, and vice versa for low rainfall. Jankowska et al. (2012) reveal that underweight and anaemia variables were not associated with water balance index in Mali, while Ledlie et al. (2018) find no consistent relationship between wasting (WHZ) for children aged 0-24 months and the rainfall shock in Ethiopia. Hirvonen et al. (2020) and Hagos et al. (2014) confirm the same in Ethiopia; wasting (low WHZ) was unrelated to rainfall or drought and temperature except for severe wasting which was positively related with rainfall quadratic term as reported by the latter study.

While the aforementioned studies focused on the current nutritional impacts, a distinct set of studies on the third strand explored future impacts considering different climate change scenarios. Deschenes et al. (2009) predict that extremely high temperatures experienced during pregnancy will decrease average birth weights by end of 21st century, with high impacts among Africans. A global study by Lloyd et al. (2011) develop a model that predicted future increases in stunting due to climate change in all regions by 30-50% for severe stunting, though with higher levels in South Asia and SSA. Similarly, Davenport et al. (2017) show that in 13 African countries, the risk of increased child low birth weight was lower as compared to risk of child stunting considering warming and drying conditions.

Even though climate change and weather extremes have been shown to have adverse effects on undernutrition, there is evidence of potential impact reduction through adaptation activities (Phalkey & Louis, 2016; Phalkey et al., 2015; Smith et al., 2014). Controlling for adaptation covariates, Bahru et al. (2019); Davenport et al. (2017); Shively (2017) consistently find that good access to socio-economic conditions, transport and health infrastructure, and productive safety nets helps to smooth out the adverse effects of precipitation and temperature extremes on undernutrition.

As mentioned early, this paper makes contribution to the existing body of literature by establishing the mechanisms through which the health effects of extreme weather events are realized in children. Some of the abovementioned few studies explored some possible mechanisms (Hirvonen et al., 2020; Hoddinott & Kinsey, 2001; Hu & Li, 2019; Omiat & Shively, 2020; Shively, 2017). However, to the best of our knowledge, none of the abovementioned studies examined the nutrient supply pathway and a range of agricultural as well as disease mediators.

**Conceptual framework**

Figure 2.1 presents the conceptual framework of the study. It is well established that the actual relationships between variables that results to undernutrition are usually complex, with much more pathways and linkages (Smith and Haddad 2000; Phalkey et al 2015), at both macro and microlevels (Smith and Haddad 2000). Therefore, we highlight all the possible pathways through which extreme weather events results into undernutrition in our conceptual framework.

However, the study focuses only on pathways and variables shaded in the conceptual framework, based on data availability.

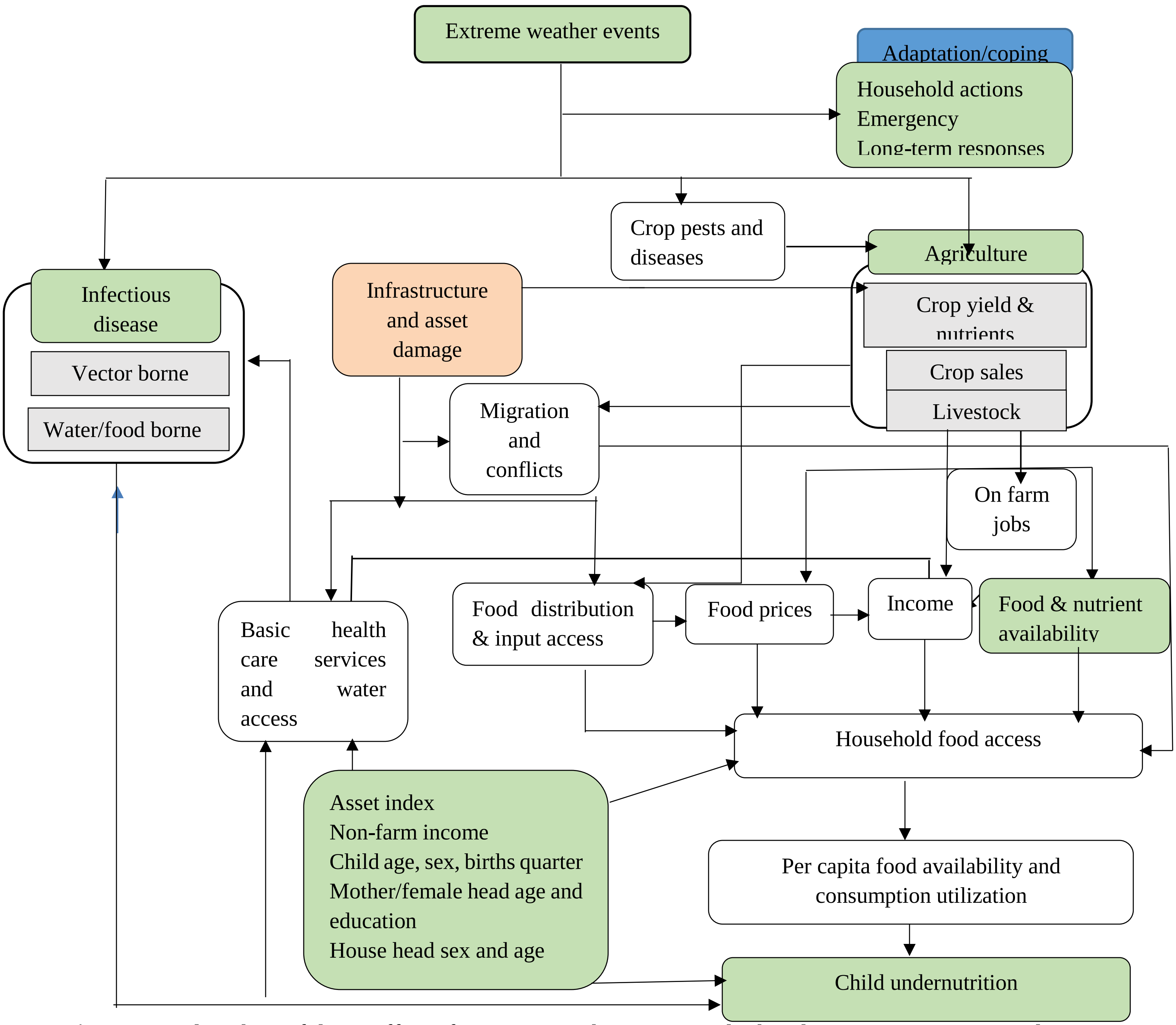


**Figure 2.1**: Flowchart of direct effect of extreme weather events and other determinants on crop and livestock, diarrhoea and fever and the indirect effects on (HAZ, WAZ & WHZ)

The arrows show direction of effect.

Source: Adapted from Phalkey et al (2015), with author modifications.

Most pathways are agricultural related and include; crop and food nutrients production, crop output market participation and livestock holdings. Pathways related to disease environment include fever as a proxy of malaria, and diarrhoea. We also explore the relationship between road infrastructure damaged by extreme weather events and undernutrition. Below is a description of the linkages starting with extreme weather events and crop or nutrient production.

Failures in seasonal rainfall is directly linked to crop failure, which further leads to not only reduction in household food availability, but also creates limitation to employment possibilities in rural areas (Haile, 2005). If unusual dry conditions occur, water supply to the crop at different phases of crop growth is limited. Dry conditions may also exacerbate soil erosion and soil moisture deficiency (Ding et al., 2011). Lack of sufficient water and nutrients for the crops and pastures may eventually lead to total crop failure or reduction in crop yield in the absence of adaptation or good agricultural practices such as; cultivation of drought resistant varieties, crop diversification or water harvesting technologies. Extremely high temperatures negatively impact crop growth and development, especially during germination and reproductive phase, potentially leading to low yields and famine (Fahad et al., 2017).

The above-mentioned extreme weather conditions may also be accompanied by pests and diseases that may destroy the crops leading to extremely low yields, which in turn affect household food consumption and income. Furthermore, extreme weather events through its effect on crop yields may affect food prices and overall stability of food systems (Wheeler & Von Braun, 2013). Extreme weather events may also have a negative effect on the quality of food crops in terms of nutrient density. For instance, during drought conditions food nutrient compositions particularly, micronutrients concentration in crops might be negatively affected (Fischer et al., 2019). Furthermore, soil moisture limitations experienced during drought conditions may inhibit acquisition and transportation of plant nutrients, and further allocation of relevant nutrients to sections of the crop that constitute food (Fischer et al., 2019). Some of the micronutrients in plants that have been found to be susceptible to climatic factors include zinc and iron (Nelson et al., 2018; Singh et al., 2012; Smith & Myers, 2018). Extreme weather events and climate change also have negative effects on the supply of energy and macronutrients such as proteins (Nelson et al., 2018; Singh et al., 2012; Smith & Myers, 2018) obtained from staple crops, as well as other crops.

Apart from crop yield and nutrient availability, economically, extreme weather events such as drought may also affect market participation, sales and operation of business that are dependent on cropping activities and water (Ding et al., 2011). The magnitude of the economic impacts due to the negative supply shocks induced by droughts are however dependent on the market structure, and the demand and supply interactions of agricultural commodities (Ding et al., 2011).

Increase in crop output have a direct effect on food availability and consumption, thus a positive effect on child nutritional status. International Fund for Agricultural Development (2014) states that "*good nutrition begins with food and agriculture*. Additionally, increased crop output may facilitate market sales. High market participation and commercialization of agriculture may have both positive and negative effects on household nutrition (Koppmair et al., 2017). Positive effect of market sales on nutritional status is through its effects on increased income (Carletto et al., 2017; von Braun, 1995) where households would be able to purchase additional and nutritious food groups that are not home produced (Koppmair et al., 2017; Ogutu et al., 2020; von Braun, 1995). Furthermore, increased revenues may also affect health care consumption, thus minimizing incidence and prevalence of infectious diseases, and improved child care (von Braun, 1995). On the other hand, crop sales may limit food availability and consumption of food from own production (Ogutu et al., 2020), in cases where crop income is spent on other needs rather than on health and nutrition improvement (Koppmair et al., 2017).

As is the case with crop output, increase in micronutrients are expected to have a positive effect on child health and vice versa for decreases. Micronutrients such as zinc, iron and vitamin A are important nutrients globally and are particularly of public health concern in developing countries (Gibson, 2006; Nelson et al., 2018; Singh et al., 2012). The aforementioned micronutrients are ranked among top ten risk factors for illness (Singh et al., 2012), and are projected to remain a problem in 2050, especially in poorest nations as compared to richer countries (Nelson et al., 2018). Insufficient intake of these mineral nutrients and vitamins, especially zinc deficiency affects human health especially child growth and development thus leading to stunting (Fischer et al., 2019; Gibson, 2006; Rivera et al., 2003), wasting (Fischer et al., 2019; Ramakrishnan et al., 2009) and underweight (Gibson, 2006). In fact, the prevalence of child stunting is used by International Zinc Nutrition Consultative group as an indirect measure of likelihood of zinc deficiency risk, and interventions related to zinc supplements as treatment of diarrhoea and has a positive response on linear growth (Gibson, 2006).

Closely related to crop production is livestock production – the third transmission channel that we investigate. Farmers in rural areas are mainly agro-pastoralists and highly dependent on livestock. Livestock plays a significant role in rural household livelihoods and welfare in terms of food, income, asset, source of credit and also act as safety net for the poor and insurance protection. Livestock is also a good proxy of permanent income and household wealth (Hoddinott & Kinsey, 2001). Alonso et al. (2019) document the importance of livestock products on children nutrition in the early life (first 1000 days). Animal source foods such as poultry, diary, meat and fish are rich sources of proteins and micronutrients such as iron and zinc which are more bioavailable as compared to plant-based sources (Gibson, 2006; Nelson et al., 2018).

Previous studies show the sensitivity of livestock to extreme weather events (Murray-Tortarolo & Jaramillo, 2019, 2020). During periods of unusually low rainfall and high temperature, there is water scarcity, increase in animal diseases and both the quantity and quality of forage is affected (Nelson et al., 2018; Rojas-Downing et al., 2017), reducing feed intake (Nelson et al., 2018). This in turn affects negatively livestock productivity and composition of livestock products (Nelson et al., 2018), reproduction, general growth and health of the livestock (Rojas-Downing et al., 2017). Both extreme temperature, severe droughts and floods can potentially lead to death of livestock thereby reduction in total household livestock holdings.

With regards to disease environment, undernutrition resulting from infections that causes diarrhoea have been documented by Humphrey (2009). Muller and Krawinkel (2005) indicate that chronic and severe infections related to diarrhoea are the second major causes of malnutrition after inadequate supply of food nutrients. Apart from direct loss of nutrients through frequent diarrhoea episodes, other underlying pathways include; reduced micronutrients uptake (von Braun, 2020a), general reduction in food intake due to anorexia, impairment of nutrients absorption and metabolic requirement increases (Muller & Krawinkel, 2005). Extremes such as flooding alter the disease environment and might be associated with higher incidences of diarrhoea which have a distinct seasonal pattern, given that high rainfall wash away faecal pathogens and other contaminants into the water bodies (Akin et al., 1992; Rabassa et al., 2014). Some of pathogens that cause diarrhoea are positively correlated with high temperatures (Akil et al., 2014). Even though undernutrition is a risk factor to other diseases such as diarrhoea, we do not investigate this feedback effect because data on child disease was based on 30 day recall before the measurements of the children were taken, thus reducing the possibility of reverse causality.

Malaria is one of the illnesses responsible for morbidity and deaths among young children aged 6-59 months (Kateera et al., 2015). One of the major symptoms of malaria is fever. Previous literature indicates associations between malaria and undernutrition (Kateera et al., 2015), and further associations between temperature variables with malaria (Kipruto et al., 2017) as well as rainfall variables (Boyce et al., 2016; Odongo-Aginya et al., 2005) in Africa. Stagnant water from flooding activities may lead to increase incidences of vector borne diseases such as malaria. Malaria in early years of childhood years may lead to lasting undernutrition and long-term health (Gone et al., 2017).

Lastly extreme weather events such as floods may have an effect on the infrastructure, causing deterioration of transport facilities and road network (Kovács & Pató, 2014). This may have effects on food and input supply chains as well as access to health care services, with repercussions of extreme weather events experienced elsewhere as well as in areas of occurrence (Levermann, 2014). As a result, local economic chains, national markets and global trade may be affected (Levermann, 2014). Concerning relationship between infrastructure and nutrition, road access an indicator of economic development may influence nutrition through its effects on several social processes that enhance resource availability (Lopez et al., 2018). Market access in particular is enhanced by good road network and is instrumental to rural households who are either buyers or sellers in food markets, thus an important determinant of dietary diversity (Koppmair et al., 2017).

## Theoretical Framework

A child health production function framework proposed by the Cebu Study Team (Akin et al., 1992) for longitudinal data is adopted for this study for the long-term measures. This framework builds on earlier models by Rosenzweig and Schultz (1983) and is estimated as follows;

$$H_{it} = f(H_{(t-1)}, Y_{(t-1)}, X_{it,}, \mu_{hi}) \tag{2.1}$$

Where $H_{it}$ is the health of child i at time t, $Y_{(t-1)}$ is health care usage and nutritional inputs in the previous period, $X_{ti}$ is a vector for exogenous variables that affect child health directly such as sex, age and $\mu_{hi}$ is unobserved variables that affect child health endowment, including child genetic endowment. Inclusion of lagged values of H and Y means that there may be lagged effects of these variables e.g. previous health care usage and illnesses. Apart from other individual and household variables, Cebu Study Team (Akin et al., 1992) indicate that climate variables are among the exogenous variables in growth and morbidity equations. Effect of some exogenous variables on health are majorly through their effect on other variables (Akin et al., 1992). Therefore, weather extreme variables in our study are assumed to affect the mediator variables in the outlined health production function. In this study, weather variables therefore enter as covariates for mediators in the health production function. We focus on agricultural related channels particularly crop productivity, macro and micronutrient supply as well as livestock holdings as the potential pathways though which extreme weather events affect child health. We also control for disease pathways.

## 2.3 Materials and methods

### 2.3.1 Data Sources

**Uganda National Panel Survey (UNPS)**

The study uses the four waves (2009-2014) of the UNPS, a national representative survey conducted and funded by Government of Uganda through Uganda Bureau of Statistics (UBOS) and World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS –ISA) in Uganda. Data was from three questionnaires administered in all the surveys. The household (HH) level and community questionnaires were administered once per year, and agriculture questionnaires administered twice in order to accurately capture harvest information (Uganda Bureau of Statistics, 2006, 2013). Household questionnaire consisted of 17 sections covering information on all possible HH socio-economic information including individual health shocks, children's anthropometry, weather shocks, road infrastructure and transport services, consumption expenditure, food security and other welfare indicators. Agriculture questionnaire comprised of a total of 10 modules capturing information on HHs land holdings, crops grown, input and technology use, quantities of agricultural produce and livestock information. For the community questionnaire, we only use data on community-level market access.

These datasets were selected because of their representativeness at national level with the samples drawn from all regions (East, West, North and Central) of Uganda, and in both urban and rural areas. However, this study targeted rural sampled households only since they are the most vulnerable to extreme weather events, and depend on rainfed agriculture for their food, income and livelihoods. An important feature of this dataset is that households' geographical locations were geo-referenced. This enabled us to match households within a given enumeration area with weather specific information. Furthermore, the households and individuals in the different waves were linked through unique, household identifiers and individual identifiers since tracking was not only done at household level but also at individual level.

Sampling was done through two stage stratified cluster sampling and the survey design in the different waves was maintained as the same. A third of the total households sampled (i.e. 3, 123) from 322 enumeration areas who were interviewed in the baseline panel 2005/06 were tracked, followed and re-interviewed in subsequent waves to ensure consistency (Uganda Bureau of Statistics, 2013). However, due to attrition rates of 15-25% and sample refresh that was introduced in 2013/2014 wave, the panels were unbalanced. Moreover, since our sample is composed of children aged 7-59 months, a child automatically dropped out of the sample if they became older than 59 months given that the anthropometric measures were not taken for older children. Children with z scores beyond the required WHO limit also dropped automatically during computation due to the fact that the measures were not biologically feasible for the different undernutrition measures. This study uses data from 3794 distinct children, who appeared either in one or several waves. For HAZ estimations, we use data on children appearing at-least in two waves, in order to capture lagged effects of child health inputs and investments.

**Weather data**

Rainfall datasets comprise the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) data version 2 for a time period ranging from 1981 to present and measured in millimetres (Funk et al., 2015). The CHIRPS product was developed by the United States Geological Survey (USGS) Earth Resources Observation and Science Centre scientists. The product provides up-to-date, reliable and complete data sets for drought monitoring and trend analysis. The CHIRPS is also advantageous for its high spatial resolution (0.05°×0.05°) (Funk et al., 2015; Poméon et al., 2017). Additionally, it is the only long-term spatial rainfall dataset with both satellite and in-situ rainfall station data (Funk et al., 2015; Haile et al., 2018).

Monthly surface temperature dataset was retrieved from Moderate Resolution Imaging Spectroradiometer (MODIS). Spatial and temporal extent of the datasets is global, from 2000 to present and values are also in the same 0.05° longitude/latitude climate modelling grid (Hooker et al., 2018; Wan et al., 2015), matching the rainfall dataset. These datasets were developed by National Aeronautics and Space Administration (NASA) in collaboration with USGS. The downloaded monthly temperature (2000-2014) and rainfall datasets (1981-2014) were processed in QGIS software and used to construct weather indices described in the next section.

### 2.3.2 Data variables

The main dependent variables in studying the effect of weather variables on child nutritional outcomes are the standardized z scores derived from the anthropometric measures of body height and weight in relation to sex and age of children aged 7 to 59 months old. Specifically, three measures: child HAZ, WHZ and WAZ are used. These indicators are created by comparing age, sex, height/length and weight of the sampled children with reference data for 'healthy' children for the US population, as recommended for international comparisons by the WHO (Alderman, 2000; O'Donnell et al., 2010). The three outcomes measure short-term or current status of nutrition (WHZ), long-term (HAZ) nutritional status changes and a mixture of both (WAZ) (O'Donnell et al., 2010). From our sampled children, correlations between HAZ and WAZ, WAZ and WHZ were evident while no correlations were found between WHZ and HAZ (Figure 2.2). The HAZ is usually related to past chronic or frequent illness and nutritional deficiencies and represents cumulative linear growth, with the extreme scores in comparison to the standard reference group denoting stunting (O'Donnell et al., 2010). Wasting and underweight are usually measured by low WHZ and WAZ respectively with cutoffs of -2. However, in the regression model the respective z scores are used as continuous variables in STATA 14 analysis software.

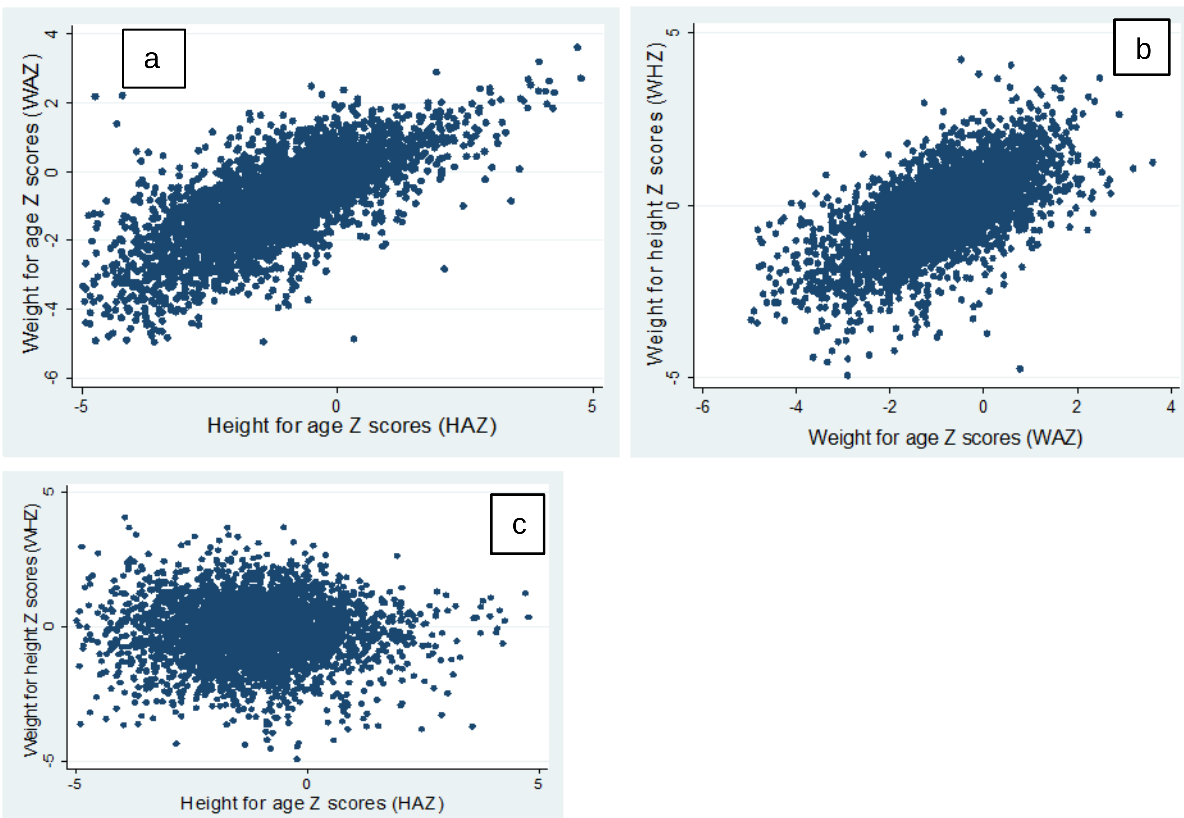


**Figure 2.2**: Two-way scatter plots on correlations between different child anthropometrics

HAZ and WAZ (a), WAZ and WHZ (b) and, HAZ and WHZ (c)

The main hypothesized pathways through which the weather variables affect the child health outcomes include; selected macro and micronutrients key to child growth and development. We use recommended units of measurement for each nutrient type and transformed into logarithm value. Mean crop productivity, measured in kilograms per acre and transformed into logarithm values and tropical livestock units (TLU), a weighted measure of all livestock groups[5] are used as measures for crop production and livestock holding respectively. Other intermediate outcomes captured by a dummy variable include; crop sales (if households crop sales value was greater than 1 in either season), and diseases proxies such as child fever and child diarrhoea, which were equal to 1 if a child experienced the specific condition 30 days before the interview date and 0 if otherwise.

We use the food composition tables (Hotz et al., 2012) and LSMS harvest data to construct the nutrient variables for each household from the list of crops harvested, including cereals/grains, beans, nuts and seeds, vegetables, roots and tubers, and fruits. Since our nutrient calculations are at crop harvest module rather than food consumption module, nutrient composition of foods harvested are considered in their raw forms. Studies that estimated micronutrient availability indicate similarities between micronutrient availability and consumption data (Schmidhuber et al., 2018).

Agricultural production in Uganda is the main gateway and pathway for domestic food consumption and dietary intake among majority of the households (Muggaga et al., 2022). Home own agricultural production usually shapes household food consumption, especially in rural areas and its most likely that most households mostly depend on own food production to meet their nutrient requirement. However, it's important to note that in certain circumstances own agricultural production does not necessarily translate into adequate nutrient intake. For instance, a household may produce adequate nutrients but nutrients may be lost through post-harvest losses, poor storage or households may sell most of the produce thereby limiting adequate consumption (Marivoet & Ulimwengu, 2022). Furthermore, households in certain regions unfavourable for agricultural production such as Karamoja might depend mostly on markets to meet their food and nutritional demands. There is limited contribution of own agricultural production to household nutrients demands in this sub-region (Muggaga et al., 2022). However, due to poverty levels, most households do not have the purchasing power and might consume very limited food crops. Therefore, it would have been be ideal to focus on both production and actual consumption of nutrients.

Marivoet and Ulimwengu (2022) considered nutrient production adequacy which measures local production capacity to meet nutrient and energy requirement at the minimum and nutrient market adequacy which measures aggregate accessibility to adequate nutrients with the later measure relying on the quantity of nutrients consumed. Overall accessibility of nutrients is increased in regions experiencing production shortages with better market integration between regions. In summary, accessibility can only be increased, if there is sufficient supply of nutrients in neighbouring regions, and increase in overall availability of nutrients is the number one and straightforward recommended strategy (Marivoet & Ulimwengu, 2022). Indeed, weather changes will first affect production, whether agricultural or livestock, consequently affecting consumption.

[5] *Different weights for the different cattle groups (cows, calves, heifers, bulls, oxen), small animals (goats, sheep, pigs) and poultry (chicken, broiler, layers, growers, ducks, geese and rabbits)*

Therefore, estimation of effects of weather on nutrient production first is the key step towards understanding the adverse effects of weather changes on nutrients and policy options in minimizing these effects.

We focus on one macronutrient (protein), two micronutrients (vitamin A and zinc) and total energy from foods measured by calories. The choice of these nutrients is informed by their importance to human nutrition and health, particularly on child growth and development. To enhance comparability across different household sizes and against the recommended daily nutrient intake, as well as ease of understanding, we compute daily average per-capita nutrient supply for each nutrient type. This variable is calculated by aggregating the nutrient quantities of selected nutrients from different crops at household level for both seasons in Uganda for each survey year, and then divided by household size and number of days in a year. Figure 2.3 shows a declining trend in daily supply of most nutrients over the years. This decline is more evident in regions that are known to experience extreme weather events such as in the north, south and east parts of Uganda.

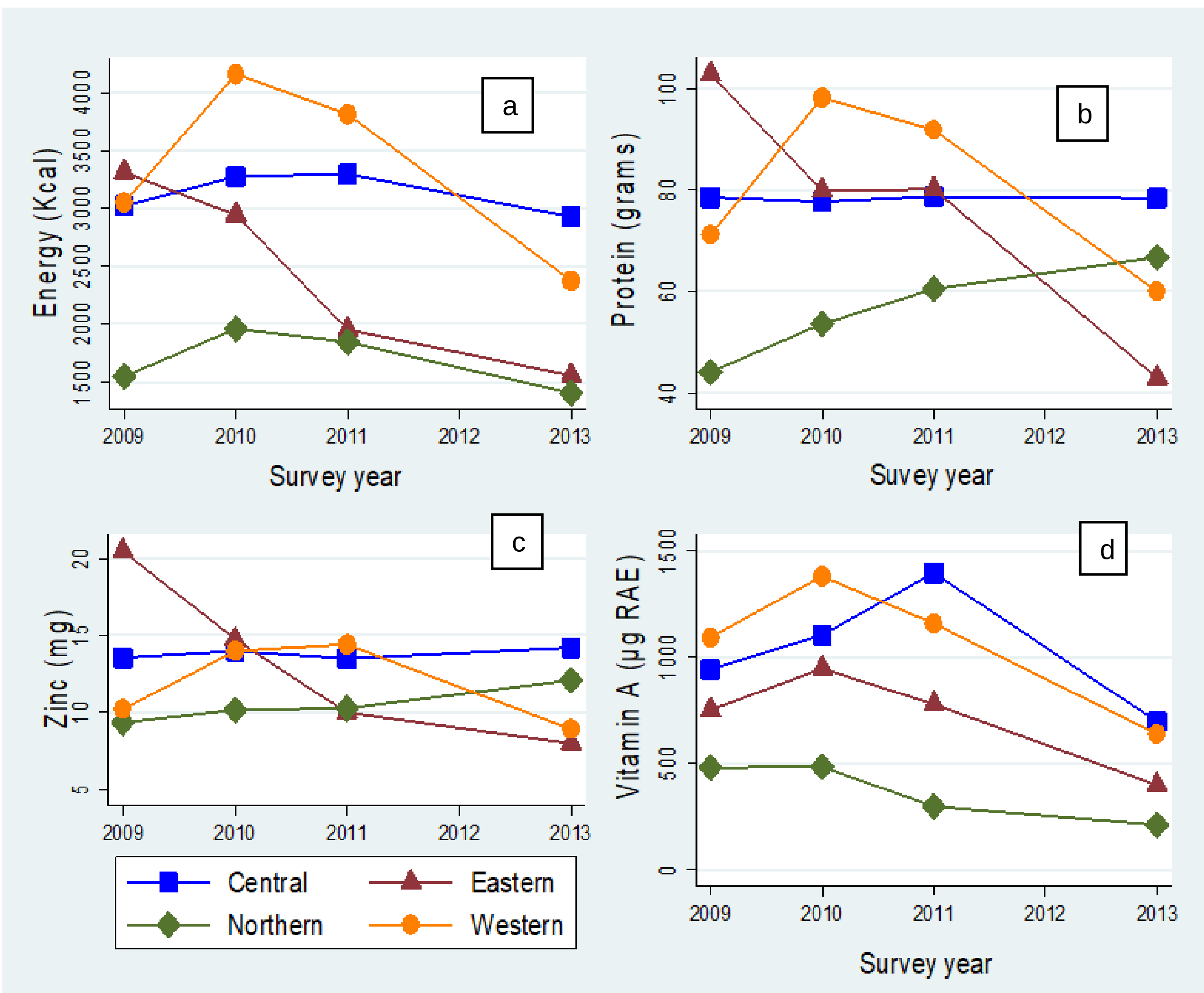


**Figure 2.3:** Plant based macronutrients and micronutrients availability

Protein and zinc supply were stable in central Uganda, while protein supply in the northern region show an increasing trend. The average value of calorie supply over the survey waves was 2549 kcal per capita per day. This value is consistent to values reported by Antonelli et al. (2020) for Uganda and Gebremedhin and Bekele (2021) for East Africa between 2010-2017. Average protein supply value of 71grams per person per day were similar to Gebremedhin and Bekele (2021) estimates while Vitamin A mean value of 757 μg Retinol Activity Equivalents (RAE) was almost double those reported by Schmidhuber et al. (2018). Average zinc values of 12 mg was slightly above the Recommended Dietary Allowance (Trumbo et al., 2001). The lag values of these nutrients were a bit higher. For convenience and reduction of skewness, logarithm values of the lags were used in the different estimations.

The variables of interest in this study are the different weather extreme variables. Since the impacts of extreme weather events on child health, nutrition and income will unfold over several seasons and with lags (Thai & Falaris, 2014), several weather indices including the lagged variables and cumulative ones are created. Statistical z scores are used in construction for both rainfall and temperature indicators to enhance comparability. The formula used for z-scores is represented as follows;

$$z_{it} = \frac{X_{it} - \bar{X}_{it}^{LTM}}{\sigma_{it}^{LT}} \tag{2.2}$$

Where $X_{it}$ is the monthly temperature or seasonal rainfall amounts (sum of rainfall received in the four months) recorded in an enumeration area/ household/child $i$ in year, $\bar{X}_{it}^{LTM}$ is the historical monthly average temperature or seasonal rainfall averages corresponding the specified months that fall within respective seasons for household/child $i$ in year $t$ and $\sigma_{it}^{LT}$ is the long-run standard deviation (SD) of household/child $i$ in year $t$. FEWS NET seasonal calendar for a typical year in Uganda is used to define the four respective months in first and second planting and growing seasons, and the eight months for the one in the Northern region.

For precipitation, we develop z scores of the total seasonal rainfall amounts (in mm) received during the main planting and growing season (first season), and second season separately, over long-term mean of the same time periods starting 1981 to the respective panel years. We then adopt z-scores cut-offs from World Meteorological Organization (WMO) Standardized Precipitation Index (SPI) with slight modifications to create a rainfall categorical variable of 5 categories instead of 7 (World Meteorological Organization, 2012). Specifically, z scores of -2 and less denote extreme dry spell, -1.99 to -1 moderately dry, -0.99 to 0.99 near normal, 1 to 1.99 moderately wet and 2+ represent extremely wet spell conditions. We further create a dummy variable of extreme dry spell which is used in empirical analysis to unfold the mechanisms (whether or not children experienced extreme dry spell variable in the main season - rainfall with z scores less than -2). The five-year count variable of dry spell is derived through summation of extreme dry spell events in both seasons for the last five years.

The distribution of HAZ scores under different rainfall regimes are shown in Figure 2.4 (a) below, which demonstrates that lower average HAZ scores were consistently recorded on children exposed to extreme dry spells. Other studies using alternative rainfall shock measure SPEI on different outcome variables include; Kubik and Maurel (2016) who did not assign any threshold while Cooper et al. (2019) used a categorical variable to focus on effects of drought and normal rainfall conditions on HAZ only. Relationship between lagged HAZ score and current HAZ score that denotes catch-up growth is shown in Figure 2.4 (b), disaggregated by dry spell.

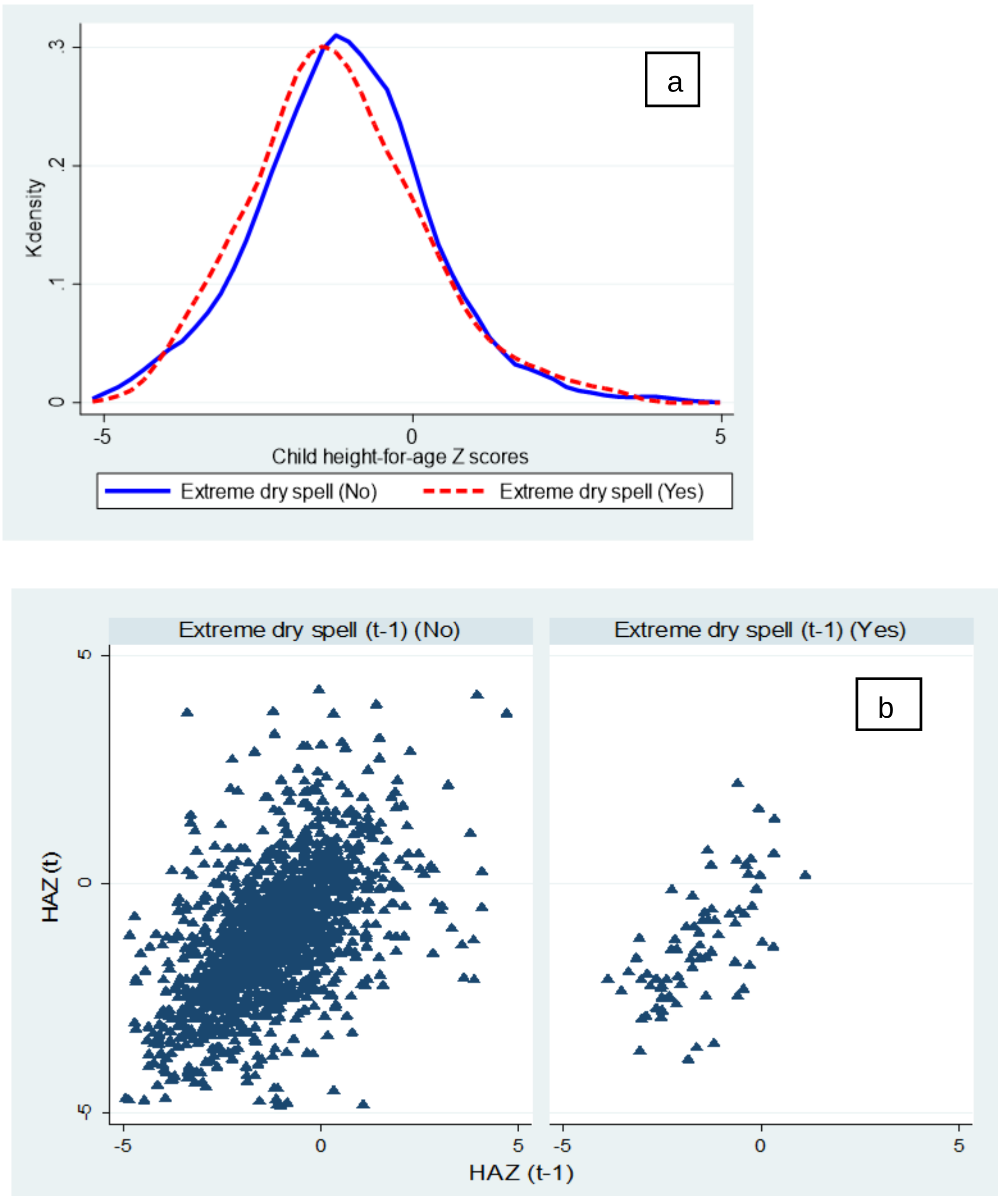


**Figure 2.4**: Relationship between rainfall categories for the first lag and children HAZ scores (a) and correlations of lagged HAZ score and current HAZ (b)

With regards to temperature, heat wave months, a proxy of heat wave is created by counting number of months in the both planting and growing seasons of the year (first season march – June) and second season (august –November) separately, where the z-scores are equal to or +1 for temperature. The respective monthly temperatures with more than 1SD above the mean have at least an average of 29°C (84.2 °F) of monthly temperature. This temperature cut-off is consistent with previous studies definition of detrimental temperatures (Heal & Park, 2014; Hu & Li, 2019; Traore & Foltz, 2017). The concept of heat wave months is adapted from Haile et al. (2018).

Spatial and temporal distribution of heat waves of the sampled areas and households constructed are shown in Figure 2.5. Heat-waves were consistently experienced in the Karamoja (North-eastern sub-region) for all time periods. It is also important to note the increase of heat-wave events in 2010 (Figure 2.5b) especially in the Southwestern region. Given that heat events exacerbate drought occurrences or sometimes occur simultaneously, more heat events recorded in 2010 are consistent with The World Bank and Global Facility for Disaster Reduction and Recovery (2019) who reported drought events in 2010. Furthermore, graphical representation in Figure 7.1 (in the appendix*)* shows that stunting rate among sampled children was highest in 2010, a period where the frequency of heat waves in the previous year was equally high. Crop productivity was low in the northern region which experienced high number of heat events.

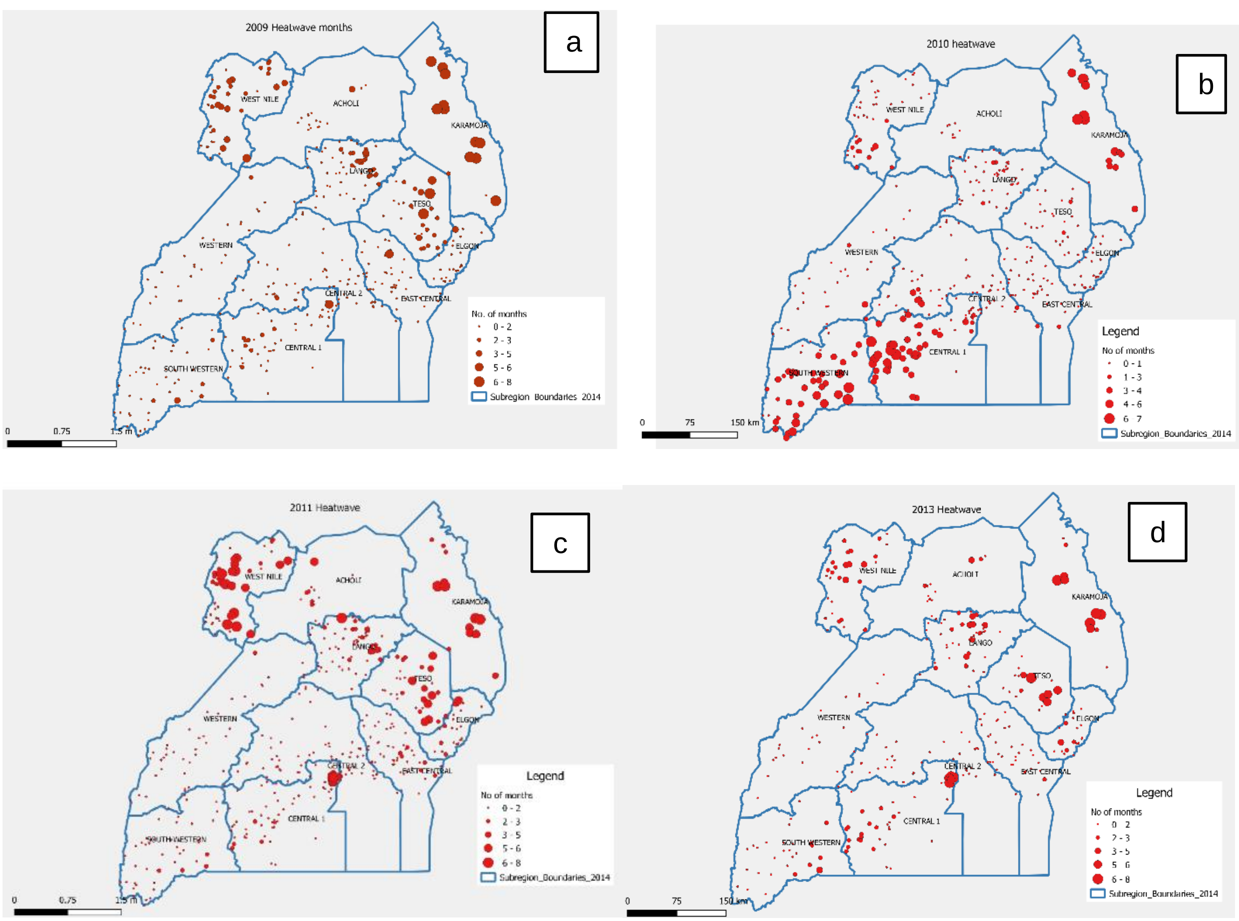

**Figure 2.5**: Maps showing the frequency of heat waves (number) months for sampled sites

The rest of the control explanatory variables used in the study are guided by literature and theory. The socio-economic variables included in the model specification are asset index, water sanitation and hygiene (WASH index) all of which are continuous variables with the latter two constructed through statistical multivariate technique; principal component analysis (PCA) that enables reduction of number of variables into smaller dimensions in the datasets (Vyas & Kumaranayake, 2006). WASH index and asset index[6] are derived separately with different combination of relevant variables related to household assets and water, sanitation and hygiene defined in ‘’ Section 9A; Housing Conditions, Water and Sanitation of the UNPS as well as the Section 14 ‘’Household Assets’’.

### 2.3.3 Empirical strategy

The aim of the study is to evaluate the causal pathways of extreme weather events on children health outcomes (HAZ, WAZ and WHZ). We therefore focus on models that explain the impact pathways. Our study deviates from most previous studies whose estimations were based on one reduced-form models, where extreme weather variables were hypothesized to have a direct effect on child undernutrition outcomes. We hypothesize that the effect of weather extremes on final child health measure under consideration in this study is indirect, occurring through multiple pathways. These pathways include crop productivity, food nutrients, crop market participation and livestock holdings that constitute the main agricultural mechanisms, and child diarrhoea and fever that define the diseases mechanisms *(see the conceptual framework*). First, extreme weather events will have a direct effect on these pathways, which act as child health inputs and investments, and these inputs will further affect child HAZ, WAZ and WHZ.

In order to trace and analyse the causal linkages between weather extremes and child health through the mentioned pathways, we adopt a simultaneous equation regression approach controlling for year and region fixed effects. Endogeneity is fundamental in specifications of simultaneous equation frameworks given that some variables in the righthand of structural equation are dependent variables in the reduced form equations (Greene, 2017). Therefore, application of ordinary least squares (OLS) on simultaneous equation system gives inconsistent and biased estimates (Wooldridge 2016). Simultaneous estimation methods improve efficiency of estimated parameters when there is correlation among dependent variables (Christ et al., 2014). Additionally, we use simultaneous approach because undernutrition is a complex problem resulting from intertwined effects of various factors. Thus, analysing the relationship concurrently

[6] Asset index was constructed from housing conditions and household assets. Housing conditions include dummies on house type (8), roofing (7), external wall (8) and floor material (5). Household asset include dummies on ownership of house, other buildings, land, furniture, household appliances, television, radio, television, generators, solar panel, bicycle, motorcycle, motor vehicle, boat, other transport equipment, jewelry, mobile phone, computer, internet access, other electronic equipment and household assets. WASH index includes dummies of the different sources of water (9), water treatment (4), toilet type (8)

provides a better understanding of the role of weather extremes, and other factors in explaining the specific undernutrition measures. Joint estimation of the equations is therefore important in our case, rather than ignoring the connection between various variables. Furthermore, separate estimation of the equations does not account for the fact that the same parameters appear in other equations and thus this information is wasted (Greene, 2017).

Given that different pathway equations are determined within the system, our treatment variables (weather extremes) on the different pathways' equations are exogenous and can be used as instruments in the different specified reduced form equations, thus solving arising endogeneity issues in the structural equations. For clarity purposes, we estimate systems of equations related to crops and diseases separately, before the joint estimation of all pathways, including livestock on HAZ in one model. First lags of respective weather variables and covariates are used in the HAZ models because HAZ is a long-term cumulative measure of health status, usually resulting from past shocks and nutritional deficiencies, therefore the current weather changes and pathway variables in the respective panels may not have an immediate effect on HAZ. First, we estimate effect of extreme weather events on one pathway at a time on HAZ model, separately with a rural child as the unit of analysis. The two-stage procedure is estimated as follows;

$$\mathrm{HAZ_{it}} = \alpha_0 + \lambda\, \widehat{\mathrm{M}}_{1\mathrm{i(t-1)}} + \theta_{1\mathrm{it}}\mathrm{CA_{i(t-1)}} + \theta_{2\mathrm{it}}\, \mathrm{X_{i(t-1)}} + \theta_{3\mathrm{it}}\mathrm{Ch_{it}} + \vartheta_{\mathrm{it}} + \varepsilon_{1\mathrm{it}} \tag{2.3}$$

$$\mathrm{M_{1i(t-1)}} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{i(t-1)}} + \theta_{1\mathrm{it}}\mathrm{CA_{i(t-1)}} + \theta_{2\mathrm{it}}\, \mathrm{X_{i(t-1)}} + \vartheta_{\mathrm{it}} + \varepsilon_{2\mathrm{it}} \tag{2.4}$$

The dependent variables in the two equations include; $M_{1i(t-1)}$ and $\mathrm{HAZ_{it}}$ in the first and second stage respectively. $M_{1i(t-1)}$ is the mediator variable that represents the specific child health inputs (nutrient supply or agriculture productivity or livestock holdings), and $\mathrm{HAZ_{it}}$ is the main outcome variable estimated as continuous measure of overall child health. All specified mediator variables above are continuous variables with nutrients and agricultural productivity converted to logarithm values. TLU variable is a weighted measure of livestock units. We considered mediator analysis since it allows decomposition of associations into components that unveil possible causal mechanism (Shrout & Bolger, 2002). Mediation is said to happen when an intervening or mediator variable (M) explains some effect of the main explanatory variable X on the outcome (Y), such that a unit change in X is associated with a change in M and a unit change in M is associated with a change in Y (Shrout & Bolger, 2002). This is also referred to as the indirect effect of X on Y through the mediator variable. Generally, the indirect effects are mediated by at least one mediator or intervening variable, and its quantified either by subtracting the direct effects from the total effects (Bollen, 1987) or is determined by the product of the two effects, that is X to M and M to Y effects (Shrout & Bolger, 2002).

There are two types of mediation: complete mediation that occurs when the indirect effect is equal to total effect, that is, when the effect of main explanatory variable (X) on main outcome (Y) is completely mediated by the mediator variable (M) such that there is no direct effect of X on the outcome variable (Y) (Shrout & Bolger, 2002). Theories might inform if the entire effect goes through M, and if so, the theory predicts full mediation. Partial mediation occurs when the indirect effect occurring through M is smaller with the same sign, but it is not equal to the total effect (Shrout & Bolger, 2002). As such, the entire effect does not occur through M (Shaver, 2005).

Even though the initial step in mediation analysis is to determine if there is relationship between X and Y ( total effect), based on our theoretical framework, we carried out the mediation estimation but not the total effect as argued out by (Shrout & Bolger, 2002). Total effect is the sum of indirect effects and direct effects while direct effects are effects that are unmediated by other variables in the regression model (Bollen, 1987). Total effect is usually defined using reduced-form coefficients (Bollen, 1987) while indirect effect is determined effectively by employing systems of equations that considers correlation in the error terms across estimated equations (Shaver, 2005). We use 2SLS and other simultaneous equation methods to derive consistent estimates for mediation analysis because the technique is ideal given that it estimates the equations as a system and addresses the interdependence rather than estimate the equations independently of each other (Shaver, 2005).

The structural form equation (2.3) is derived directly from the underlying theory discussed before and represents the second stage estimations. The predicted inputs $\widehat{M}_{1i(t-1)}$ , appear in the second stage estimation as explanatory variables. Child health inputs $M_{1i(t-1)}$ in the first stage are influenced by extreme weather events denoted by $W_{i(t-1)}$. This latter variable capture both the occurrence and frequency of the extreme weather events during the cropping season and over the previous five years. Equations (2.4), therefore enables us to trace the effects of changes in extreme weather events on the final outcome variable. For instance, the weather extremes denoted by $W_{i(t-1)}$ do not appear in the undernutrition function (2.3), but that does not imply that changes in extreme weather events would not cause changes in the undernutrition measures. Changes in weather conditions change crop yield or nutrient supply levels which have an effect on undernutrition. All weather variables are simultaneously controlled for, in order to avoid the problem of omitted-variable bias (Letta et al., 2018; Meierrieks, 2021). Our main coefficients are $\beta$ and $\lambda$ in the reduced form equations and structural equations respectively.

Additional determinants of child health include child characteristics such as sex, age squared ( $Ch_{it}$). Other factors incorporated in both models include coping and adaptation [7] strategies $CA_{i(t-1)}$ such as savings, credit access, non-farm work, change of diet, sell of assets, formal and informal safety nets from government and friends/relatives, for coping strategies. Different improved input use and cropping patterns for adaptation such as pesticide use, crop diversification, fertilizer use, improved seed use etc. $X_{i(t-1)}$ represents a vector of other socioeconomic controls such as land size, asset index, market access and household head/ mother characteristics. $\vartheta_{it}$ , $\varepsilon_{1it}$ and $\varepsilon_{2it}$ are the unobserved time-invariant differences across locations and the error terms

[7] Adaptations strategies controlled for are mentioned by IPCC report on Impacts, Adaptation, and Vulnerability as potential adaptation options. We define adaptation based on the usage of these options in the different years.

respectively. Measurement errors, unobserved investments and genetic potential are among factors that could result into biased and inconsistent estimates. Therefor in order to address potential heterogeneity biases, we add sufficient covariates, including year and region variables in all models. More details on definition of variables is explained in the supplementary materials.

Secondly, we estimate the HAZ system of equations consisting of one structural equation and two reduced form equations related to agricultural pathways simultaneously. The regression estimation is expressed as follows;

$$\mathrm{HAZ_{it}} = \alpha_0 + \lambda\, \mathrm{M_{1i(t-1)}} + {}_{\varphi}\, \mathrm{M_{2i(t-1)}} + \theta_{1it}\mathrm{CA_{i(t-1)}} + \theta_{2it}\, \mathrm{X_{i(t-1)}} + \theta_{3it}\mathrm{Ch_{it}} + \vartheta_{it} + \varepsilon_{3it} \qquad (2.5)$$

$$\mathrm{M_{1i(t-1)}} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{i(t-1)}} + \theta_{1it}\mathrm{CA_{i(t-1)}} + \theta_{2it}\, \mathrm{X_{i(t-1)}} + \vartheta_{it} + \varepsilon_{4it} \qquad (2.6)$$

$$\mathrm{M_{2i(t-1)}} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{i(t-1)}} + \theta_{1it}\mathrm{CA_{i(t-1)}} + \theta_{2it}\, \mathrm{X_{i(t-1)}} + \vartheta_{it} + \varepsilon_{5it} \qquad (2.7)$$

The two pathway variables $M_{1i(t-1)}$ and $M_{2i(t-1)}$ on the right-hand side of the first structural equation (2.5) include either; crop yield, and crop sales in the previous year before the interview ( a dummy variable) or either crop yield and TLU. All other variables remain as earlier defined. The socioeconomic controls $X_{i(t-1)}$ in the various equations (2.5-2.7) are not identical but may overlap. Inclusion of the various controls is based on theory, for instance mother/female head and child characteristics are excluded from crop production and crop sales equation, even though they are included in the main structural equation. Only household and household head characteristics are included in the livestock model (2.7), excluding adaptation, coping and mother/child variables. Our main coefficient of interest is on the second pathway coefficients ($_{\varphi}$) and extreme weather events (β)**.**

After crop production and sales, we examine the effect of extreme weather variables on HAZ through the different disease pathways as follows;

$$\mathrm{HAZ_{it}} = \alpha_0 + \tau\, \mathrm{M_{3i(t-1)}} + \tau\, \mathrm{M_{4i(t-1)}} + \theta_{1it}\mathrm{CA_{i(t-1)}} + \theta_{2it}\, \mathrm{X_{i(t-1)}} + \theta_{3it}\mathrm{Ch_{it}} + \vartheta_{it} + \varepsilon_{6it} \qquad (2.8)$$

$$\mathrm{M_{3i(t-1)}} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{i(t-1)}} + \theta_{2it}\, \mathrm{X_{i(t-1)}} + \theta_{3it}\mathrm{Ch_{i(t-1)}} + \vartheta_{it} + \varepsilon_{7it} \qquad (2.9)$$

$$\mathrm{M_{4i(t-1)}} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{i(t-1)}} + \theta_{2it}\, \mathrm{X_{i(t-1)}} + \theta_{3it}\mathrm{Ch_{i(t-1)}} + \vartheta_{it} + \varepsilon_{8it} \qquad (2.10)$$

Most of the variables in the structural equation (2.8) are identical to equations (2.3 and 2.5), with the exception of $\mathrm{M_{3i(t-1)}}$ and $\mathrm{M_{4i(t-1)}}$ which replace the agricultural pathways. These variables are dummies that represent diarrhoea and fever incidence for child $i$ in the previous interview year $(t-1)$. Furthermore, mother/female head and child characteristics ($\mathrm{Ch_{i(t-1)}}$ are included in the respective reduced form equations for diarrhoea and fever while, adaptation and coping strategies appear only in the structural equation (2.8), and not in the disease pathway equations (2.9-2.10). In addition to separate estimations of temperature and rainfall extremes, all weather variables are simultaneously controlled for in final regressions. Furthermore, we include multiple pathways (crop yield, TLU, diarrhoea and fever), in one system of equation.

For weight measures (WAZ and WHZ), similar systems of equations and variables are estimated. The basic regressions deviate from HAZ in the following way; the production estimates and disease conditions recorded in the respective interview years are considered as opposed to the lagged effects. Furthermore, weather variables and other covariates are not lagged. We do not use lags because both undernutrition measures are short-term measures of current nutritional deficiencies, thus responsive to the contemporaneous weather extremes or extremes experienced in the interview year.

The most important element incorporated in these equations is the interactions between extreme weather events and adaptation strategies as well as other farm characteristics in the crop yield equation (2.12). The set of simultaneous equation on crop pathways (corresponding to equation 2.5, 2.6 and 2.7) is specified as follows;

$$\mathrm{WAZ_{it}} / \ \mathrm{WHZ_{it}} = \alpha_0 + \lambda\, \mathrm{M}_{1it} + {}_{\varphi}\, \mathrm{M_{2it}} + \theta_{1\mathrm{it}}\mathrm{CA_{it}} + \theta_{2\mathrm{it}}\,\mathrm{X_{it}} + \theta_{3\mathrm{it}}\mathrm{Ch_{it}} + \vartheta_{\mathrm{it}} + \varepsilon_{9\mathrm{it}} \tag{2.11}$$

$$\mathrm{M}_{1it} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{it}} + \theta_{1\mathrm{it}}\mathrm{CA_{it}} + \phi_{\mathrm{it}}\mathrm{W_{it}} * \mathrm{CA_{it}} + \theta_{2\mathrm{it}}\,\mathrm{X_{it}} + \vartheta_{\mathrm{it}} + \varepsilon_{10\mathrm{it}} \tag{2.12}$$

$$\mathrm{M}_{2it} = \alpha_0 + \boldsymbol{\beta}\, \mathrm{W_{it}} + \theta_{1\mathrm{it}}\mathrm{CA_{it}} + \theta_{2\mathrm{it}}\,\mathrm{X_{it}} + \vartheta_{\mathrm{it}} + \varepsilon_{10\mathrm{it}} \tag{2.13}$$

With inclusion of the interaction term $\mathrm{W_{it}} * \mathrm{CA_{it}}$ in equation 2.12 we are able to estimate the effects of the different adaptation strategies on crop production during household's exposure to the extreme weather events. Since the effect of weather extremes on the respective response variables is expected to be negative, we expect our main coefficient of interest on the interaction term ($\phi$) to be positive. Other coefficients of interest in the structural equations and reduced form equations are $\lambda$ , ${}_{\varphi}$ and $\beta$ respectively, as earlier mentioned in the HAZ equations. Additionally, the disease pathways specifications as well as livestock pathways and the two stage for crop nutrients are similar to those earlier defined, excluding the lags.

**Joint estimation methods and identification**

To account for endogeneity and establish the indirect effects of extreme weather events, this study adopts two different simultaneous equations methods. The instrumental variable (IV) approaches and the conditional recursive mixed process (CMP). For the former approach, we use two stage least squares strategy (2SLS) for estimations involving only one pathway variable, and three stage least squares (3SLS) for estimations with systems of equations with more than one pathway variables. These instrumental variables approaches are only applied on continuous pathway and outcome variables. Specifically, in estimations of extreme weather events on crop yields, nutrients, TLU, and the resulting effect on child HAZ, WAZ and WHZ. IV methods are ideal in overcoming biases related to measurement errors and omitted variable bias, thus enabling consistent estimates in studies of causal relationship (Angrist & Krueger, 2001). We adopt 3SLS method because it’s more efficient and consistent given that it estimates all coefficients of the whole system simultaneously accounting for both endogeneity among dependent variables, and cross equation correlations, problems that seemingly unrelated regressions and 2SLS cannot solve in isolation (Zellner & Theil, 1962). Furthermore, it enables us isolate the relevant controls in each equation, unlike 2SLS, where all controls in the second stage appear in the first stage.

Since strong instruments are needed for identification, we include exogenous variable in each pathway equation for the different systems, that are excluded from the main structural equations. So as to satisfy the exclusion criteria, and order condition of identification related to simultaneous equations (Greene, 2017; Wooldridge, 2016). The challenge is always to find a suitable valid instrument given that it should be exogenous (not correlated with unobserved factors that affect undernutrition), correlated with the endogenous variable (pathway variables; crop output, nutrients and livestock), and only affect the child undernutrition measures indirectly through the pathway variables. In our study, our main explanatory variables (extreme weather events), used in first stage estimation, were all used as possible instruments for identification of our pathway variables in the respective systems of equations. Similar instruments of weather variability have been used previously (Antonelli et al., 2020; Asfaw et al., 2016; Dercon & Porter, 2014; Omiat & Shively, 2020). We assume that weather extremes are random and exogeneous. However, even though literature documents significant effects of weather variability measures on the different pathways, we conduct the F-test of joint significance to ascertain the validity and strength of our instruments. Furthermore, we conduct endogeneity tests in 2SLS estimations to justify our choice of IV methods.

For binary pathways variables (diarrhoea, fever and crop sales) or combinations, we use CMP method which is a seemingly unrelated type of regression. The CMP of Roodman (2011) is consistent in recursive systems, ideal in fitting large families of multi-equations, conditional mixed-process estimators and multilevel equations. The methodology is appropriate in system of equations that contains a combination of structural and reduced form equations, where the variables in the later provides instruments for identification purposes in the structural equations (Baum et al., 2017; Roodman, 2011). CMP is referred to as "Mixed process” because of its flexibility in modelling simultaneous equations systems in which dependent variables contains mixed distributions such as, generalized linear response functions (binary, counts) and linear response functions in the same system (Baum et al., 2017; Roodman, 2011) as it is in our case. Our systems of equations are recursive with mixed distribution of functions (continuous for HAZ/WAZ/WHZ equations, crop production and livestock equations and binary responses for crop sales diarrhoea and fever equations). This methodology employs maximum likelihood procedure and allows estimation of all equation’s parameters in a single process, therefore, allowing estimation of cross-equation correlations of error terms (Baum et al., 2017; Roodman, 2011). The joint estimation and cross equation correlation enable us to get estimates corrected for endogeneity bias (Makate et al., 2016; Roodman, 2011). Significant values of athanrho parameters imply the presence of cross-equation correlations, and thus endogeneity due to the unobserved factors that simultaneously affect the different equations. As much as identification problem is solved in CMP by the recursive nature and covariance restrictions on each equation in the respective systems of equation. Makate et al. (2016) documents that it is always good practice to add instruments for identification in the reduced form equations.

## 2.4 Results

### 2.4.1 Descriptive statistics

Table 7.1 in the appendix summarizes the descriptive statistics of children aged between 7-59 months, extreme weather events and other covariates for mother, female head, and children households' socio-economic characteristics. In general, children had lower HAZ, WAZ and WHZ scores averaged at -1.13, -1.02 and -0.25 respectively. Approximately 27 % of children were stunted, 21% underweight and only 7 % were wasted. Children were 32 months of age on average, and half of them were female. The proportion of children born in each quarter of the year was almost similar, and 89% of the children lived with their biological mothers in the households. Mother or female head age was about 35 years and 22% never attended school. Household heads were older with 41 years and had 6 years of education. The dependency ratio was 194%. Fever was the most common symptom reported by approximately a third of the total children. However, only 9% of the sampled children experienced diarrhoea episodes. Children were from relatively poor households, given that the asset index was averagely -0.77, total off-farm income was less than 200,000 Uganda shillings (UGX) per month and the average TLU was 2.31 units. Moreover, household's access to WASH was generally poor with a mean index of -0.54. The average farm size of households was 2.47 acres with over three quarters of the households participating in crop output market sales. Only 46% of the households resided in districts where input and output markets were within Local council 1 (LC1).

Extreme dry spell conditions in the first and second season as well as the first lag were experienced by utmost 5% of the sampled children on average. Heat waves were also experienced by sampled children. On average, they experienced one month of heat in the first, and second seasons. Approximately 14% of the households indicated that their roads were inaccessible because of bad weather. Due to the negative effects of extreme weather events, households of sampled children engaged in different coping strategies both anticipatory as well as reactive. Undesirable coping strategies such as involuntary change of the diet was the most common strategy used by 22% of the respondents, followed by savings (an *exante* strategy) practiced by 20% of total respondents. Households also engaged in multiple practices such as receiving aid/help from government, friends and relatives and more off –farm work. Household cultivated 4 crops on average each season and a third of the households used water harvesting technologies in their farms, 20% used improved seed, and 12% used organic fertilizers and pesticides and only 4% used inorganic fertilizers.

### 2.4.2 Empirical findings

**Effect of extreme weather events on HAZ through the nutrients supply and crop productivity pathway**

The main empirical findings on the impact estimates of extreme weather events on HAZ through the crop nutrients production and supply mechanisms are presented in Table 2.1. The effect of extreme weather events on HAZ is indirect, through various channels. First, we discuss the effect of weather extremes on these channels, which are in turn our main explanatory variables into the child health production. As much as we control for a bunch of covariates in the different equations (*see descriptive statistics in Table 7.1*), for clarity purposes, we only report and discuss results on our main variables of interest. Furthermore, models accounting for joint effects of extreme weather variables in the first stage are preferred and presented.

Holding other factors constant, the effect of most extreme weather events variables was negative and statistically significant on crop yield, macronutrients and micronutrients , except vitamin A which was negatively affected by only cumulative heat and drought events, over the last five years. The pathways variables were measured in logarithms, implying that that a dry spell in previous year main planting season reduced calorie supply by 59.4% and an additional dry spell in the previous 5 years reduced calorie supply by about 30% as shown in column 1. Columns 3, 5 and 7 show the effect of weather extremes on protein, zinc and vitamin A supply. In all nutrient's models, we observe statistically significant negative effects. The largest negative effect was from dry spells in the last season, which reduced protein supply by 34% and zinc supply by 29%. An additional dry spell in the previous 5 years reduced protein supply by 13% and zinc supply by 8%. Similar negative effects of dry spell were observed on crop yields. For instance, occurrence of drought events in the prior year main season reduced crop productivity by 73% while an additional dry spell in the last 5 years reduced crop yield by 11%.

With regards to heatwaves, negative and significant effects on nutrients were only observed on heatwave frequency over the previous five years, and not heatwave experienced during the previous year main season. An additional heatwave month reduced calorie, protein and zinc and by 3%, 2% and 1%. Similarly, an additional heatwave in the last 5 years reduced crop yield by 2.3% while heatwave in the previous year planting season reduced crop yield by over 20%. There were no significant effects of heatwave in the previous year on calorie, protein and zinc supply models, even though the effect was negative as expected.

Negative effects of extreme weather events on vitamin A supply were only observed on the longer-term count measures of weather extremes, and not for short-term measures. For instance, an additional heatwave and dry spell in the last 5 years reduced vitamin A by 6% and 20% respectively. However, a heat wave in the last year planting season increased vitamin A intake by 26%, while a dry spell increased by 48%. A possible explanation to the positive effect could be due to the resistance and tolerance of some of vitamin A rich foods such as leafy vegetables, pumpkins and fruits to drought stress. Amaranth is one of the leafy vegetables being promoted in

East Africa as a drought tolerant crop (Alemayehu et al., 2015). Furthermore, ripened mangoes prefer warm temperature and some varieties can tolerate short-term weather stress e.g. drought for up to 8 months (Bally, 2006). Additionally, (Fischer et al., 2019) reported that mild drought might be beneficial for some nutrient concentrations in food crops.

First stage F-statistic for (joint) significance tests which measures the relevance of instruments was greater than 10 in all estimations, implying that extreme weather events were strong instruments for nutrients supply and crop yield. In the second stage estimations, effects of various nutrients and crop yield on child HAZ are presented. Since our main explanatory variables (pathways) were measured in logarithms and our main outcome (HAZ) in standard deviations, interpretations of our coefficients are based on level-log estimations. An increase in calorie supply by 10 percent in the prior interview year led to an improvement in HAZ by 0.021 standard deviations and a 10 percent increase in protein supply increased HAZ by 0.037. The effect of zinc on HAZ was greater than the effect observed on macronutrients, vitamin A and crop yield. Precisely, a 10% increase zinc availability led to an increase in HAZ scores of about 0.056 standard deviation. This effect size was more than double to observed effects of calories (0.021) and triple the effect of crop yield (0.017). However, the coefficients of vitamin A, though positive, were insignificant in the second stage.

In summary, the results on the effect of the selected macronutrients, micronutrients on child HAZ remained positive and significant in most estimations in the second stage. These results provide evidence on the importance of food nutrients, especially zinc and protein on HAZ for rural children. In the first stage, effect of extreme weather events was negative and of higher magnitude for precipitation extremes, implying that droughts are detrimental to both quantity and quality of crops, in terms of food nutrients. Further, we observe that some nutrients were very sensitive to extreme weather events occurring during the immediate cropping season while others though tolerant to short-term changes, responded negatively to more cumulative extreme weather events.

**Table 2.1:** Effect of extreme weather events on HAZ, through nutrient supply and crop productivity channels (2SLS estimation)

| VARIABLES | 1st stage lnCalories (t-1) | 2nd stage HAZ | 1st stage lnProtein (t-1) | 2nd stage HAZ | 1st stage lnZinc (t-1) | 2nd stage HAZ | 1st stage lnVitamin A (t-1) | 2nd stage HAZ | 1st stage Crop yield (t-1) | 2nd stage HAZ |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| ***Nutrients*** | | | | | | | | | | |
| lnCalories (t-1) | | 0.210*** | | | | | | | | |
| | | (0.078) | | | | | | | | |
| lnProtein (t-1) | | | | 0.373** | | | | | | |
| | | | | (0.153) | | | | | | |
| lnZinc (t-1) | | | | | | 0.564** | | | | |
| | | | | | | (0.233) | | | | |
| lnVitamin A (t-1) | | | | | | | | 0.092 | | |
| | | | | | | | | (0.084) | | |
| Crop yield | | | | | | | | | | 0.166* |
| | | | | | | | | | | (0.086) |
| ***Extreme weather events*** | | | | | | | | | | |
| Dry spell (5-year counts)[8] | -0.295*** | | -0.127*** | | -0.080*** | | -0.199*** | | -0.109** | |
| | (0.039) | | (0.033) | | (0.028) | | (0.071) | | (0.051) | |
| Dry spell main season (t-1) | -0.594*** | | -0.344*** | | -0.285** | | 0.480* | | -0.732*** | |
| | (0.156) | | (0.131) | | (0.112) | | (0.282) | | (0.202) | |
| Heatwave main season (t-1) | -0.041 | | -0.034 | | -0.032 | | 0.256*** | | -0.201*** | |
| | (0.045) | | (0.037) | | (0.032) | | (0.080) | | (0.058) | |
| Heatwave (5-year counts) | -0.025*** | | -0.015** | | -0.009* | | -0.058*** | | -0.023** | |
| | (0.007) | | (0.006) | | (0.005) | | (0.013) | | (0.009) | |
| ***Coping strategies*** | | | | | | | | | | |
| L1. Savings | 0.190** | 0.078 | 0.088 | 0.086 | 0.042 | 0.096 | 0.094 | 0.119 | 0.136 | 0.102 |
| | (0.090) | (0.104) | (0.075) | (0.106) | (0.064) | (0.107) | (0.162) | (0.103) | (0.116) | (0.103) |
| L1. Nonfarm work | -0.096 | 0.266** | -0.132 | 0.297** | -0.061 | 0.284** | 0.146 | 0.215* | -0.242* | 0.287** |
| | (0.100) | (0.114) | (0.084) | (0.119) | (0.072) | (0.120) | (0.181) | (0.113) | (0.130) | (0.118) |
| L1. Government aid | -0.893** | 0.176 | -0.654* | 0.194 | -0.362 | 0.150 | -0.696 | -0.134 | -0.958* | 0.010 |
| | (0.424) | (0.501) | (0.355) | (0.518) | (0.304) | (0.521) | (0.764) | (0.490) | (0.549) | (0.493) |
| L1. Credit access | 0.127 | 0.150 | 0.119 | 0.131 | 0.035 | 0.156 | -0.031 | 0.195 | 0.440 | 0.101 |

[8] We also lag this to match previous year production

| | (0.213) | (0.243) | (0.178) | (0.247) | (0.152) | (0.252) | (0.383) | (0.241) | (0.275) | (0.246) |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| | lnCalories (t-1) | HAZ | lnProtein (t-1) | HAZ | lnZinc (t-1) | HAZ | lnVitamin A (t-1) | HAZ | Crop yield (t-1) | HAZ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| L1. Sell of assets | 0.219 | 0.217 | 0.187 | 0.201 | 0.085 | 0.223 | 0.216 | 0.258 | -0.157 | 0.313 |
| | (0.169) | (0.193) | (0.142) | (0.197) | (0.121) | (0.200) | (0.304) | (0.192) | (0.219) | (0.191) |
| L1. Involuntary change of diet | -0.066 | -0.150 | 0.014 | -0.168* | 0.041 | -0.185* | 0.020 | -0.175* | -0.097 | -0.145 |
| | (0.083) | (0.094) | (0.069) | (0.095) | (0.059) | (0.098) | (0.149) | (0.094) | (0.107) | (0.095) |
| L1. Friends & relatives aid | 0.073 | -0.007 | 0.018 | 0.001 | 0.007 | 0.003 | -0.639*** | 0.066 | -0.153 | 0.031 |
| | (0.136) | (0.155) | (0.114) | (0.158) | (0.097) | (0.161) | (0.245) | (0.165) | (0.176) | (0.155) |
| ***Adaptation & farm activities*** | | | | | | | | | | |
| L1. Number of crops | 0.127*** | -0.016 | 0.115*** | -0.032 | 0.094*** | -0.043 | 0.384*** | -0.019 | 0.157** | -0.014 |
| | (0.020) | (0.026) | (0.017) | (0.031) | (0.015) | (0.035) | (0.036) | (0.042) | (0.026) | (0.028) |
| L1. Improved seed | 0.157* | 0.021 | 0.140* | 0.000 | 0.126** | -0.019 | 0.037 | 0.048 | 0.151 | 0.024 |
| | (0.087) | (0.099) | (0.073) | (0.102) | (0.062) | (0.106) | (0.156) | (0.099) | (0.112) | (0.099) |
| L1. Pesticides | 0.494*** | -0.100 | 0.525*** | -0.188 | 0.453*** | -0.246 | 0.060 | -0.009 | 0.448*** | -0.058 |
| | (0.109) | (0.129) | (0.091) | (0.148) | (0.078) | (0.164) | (0.196) | (0.123) | (0.141) | (0.126) |
| L1. Organic fertilizer | -0.065 | 0.124 | -0.132 | 0.158 | -0.154** | 0.195 | 0.363* | 0.062 | -0.104 | 0.118 |
| | (0.104) | (0.119) | (0.087) | (0.123) | (0.074) | (0.130) | (0.187) | (0.120) | (0.134) | (0.118) |
| L1. Inorganic fertilizer | 0.045 | -0.270 | 0.037 | -0.273 | 0.026 | -0.274 | -0.167 | -0.234 | 0.367* | -0.318* |
| | (0.157) | (0.179) | (0.131) | (0.182) | (0.113) | (0.186) | (0.283) | (0.179) | (0.203) | (0.182) |
| ***Other variables*** | | | | | | | | | | |
| L1. Market access | 0.488*** | 0.034 | 0.229*** | 0.051 | 0.143* | 0.051 | 0.717*** | 0.132 | 0.409*** | 0.071 |
| | (0.104) | (0.128) | (0.087) | (0.130) | (0.074) | (0.133) | (0.186) | (0.129) | (0.134) | (0.131) |
| L1. Farm area | 0.020** | 0.014 | 0.010 | 0.015 | 0.013** | 0.011 | 0.006 | 0.018* | -0.121*** | 0.038*** |
| | (0.009) | (0.010) | (0.007) | (0.010) | (0.006) | (0.011) | (0.016) | (0.010) | (0.011) | (0.015) |
| Other variables, year & region | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First stage F statistics [9] of instruments | 53.02*** | | 20.35*** | | 12.57*** | | 14.23*** | | 25.919*** | |
| Durban statistics | 7.327*** | | 5.739** | | 6.033** | | 1.619 | | 2.684 | |
| Wu-Hausman F statistics | 7.144*** | | 5.589** | | 5.876** | | 1.571 | | 2.607 | |
| Observations | 1,311 | 1,311 | 1,311 | 1,311 | 1,311 | 1,311 | 1,311 | 1311 | 1311 | 1311 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[9] Measures relevance of the instruments

**Effect of nutrients supply and crop productivity pathways on HAZ, by child gender**

Table 2.2 presents results of different mediator variables on child HAZ based on 2SLS estimations, disaggregated by gender of the child. Calories, proteins and zinc had significant effects on HAZ of the boys, and not girls HAZ. However, the magnitude of coefficients of these nutrients were larger among girls than boys.

**Table 2.2**: Second stage estimations of pathway variables on child HAZ, by child sex

| Variables | | HAZ (t) | | | |
|---|---|---|---|---|---|
| **Panel A: Boys** | (1) | (2) | (3) | (4) | (5) |
| lnCalories (t-1) | 0.177** | | | | |
| | (0.085) | | | | |
| lnProtein (t-1) | | 0.317* | | | |
| | | (0.164) | | | |
| lnZinc (t-1) | | | 0.481* | | |
| | | | (0.262) | | |
| lnVitamin A (t-1) | | | | 0.150 | |
| | | | | (0.097) | |
| lnCrop yield (t-1) | | | | | 0.125 |
| | | | | | (0.086) |
| Other variables | Yes | Yes | Yes | Yes | Yes |
| Observations | 678 | 678 | 678 | 678 | 678 |
| **Panel B: Girls** | | | | | |
| lnCalories (t-1) | 0.240 | | | | |
| | (0.154) | | | | |
| lnProtein (t-1) | | 0.359 | | | |
| | | (0.281) | | | |
| lnZinc (t-1) | | | 0.536 | | |
| | | | (0.378) | | |
| lnVitamin A (t-1) | | | | -0.029 | |
| | | | | (0.136) | |
| lnCrop yield (t-1) | | | | | 0.252 |
| | | | | | (0.189) |
| Other variables | Yes | Yes | Yes | Yes | Yes |
| Observations | 633 | 633 | 633 | 633 | 633 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Adaptation strategies, coping strategies and the role of markets on nutrients and child HAZ**

Despite the negative effects of temperature and precipitation extremes on nutrients supply and crop productivity, household employed different adaptation strategies to reduce the deleterious effects of weather extremes on crop production, and enhance consumption smoothing. Coping strategies such as precautionary saving was positively and significantly associated with calorie supply, while the relationship between formal safety nets and calorie supply was negative as shown in Table 2.1. However, the coefficients of both savings and government aid remained positive on HAZ in most estimations, even though it was insignificant. The negative effect of safety nets on calorie supply can be explained as follows, programs such as food or income transfers are usually targeted for food insecure households experiencing shocks such as bad weather or conflicts. In this case, such households are unable to meet their food requirements through crop production or home-produced foods. Therefore, such programs can only have a direct impact on HAZ and not crop or nutrient production. Savings on the other hand can be used to purchase agricultural inputs or food, thus a positive effect on both crop production and HAZ. Other strategies such non-farm work, sell off assets and credit access had positive effects on HAZ, while involuntary change of diet had negative and significant effect on HAZ. Specifically, participation in nonfarm work consistently increased HAZ scores by as much as 0.29 standard deviation while change of diet reduced HAZ scores by around 0.19 standard deviations as shown in Table 2.1.

Even though we control for adaptation in both stages of the 2SLS estimations, our discussion is based on the first stage estimates on crop pathways, since adaptation is more relevant and have a direct effect on crop production. Generally, the coefficients of crop diversification, improved seed and pesticides use were positive and significant in most estimations as shown in Table 2.1. For instance, an increase in one crop planted increased calorie, protein, zinc, vitamin A and crop productivity by 13%, 12%, 9%, 38% and 16% respectively. Households that used improved seed recorded significantly higher calorie, protein and zinc production, while pesticide use was positively associated with all nutrient's and crop productivity, except vitamin A. On the other hand, organic fertilizers led to significantly higher vitamin A supply while inorganic fertilizer was associated with better crop productivity. Further results indicate increased nutrients and crop production for children in districts where input and output markets were easily accessible. Access to the markets increased vitamin A and calorie production by 72% and 49%. Similar results in terms of coefficient sign and significance level were observed on protein, crop productivity and zinc, although the effect sizes were lower. The effect of market access on HAZ was positive in all estimations. These results indicate the importance of coping, adaptation strategies and markets in increasing crop and nutrient production and child HAZ in the presence of weather extremes.

**Effect of extreme weather events on HAZ through the crop sales and livestock holding channels**

In the previous section, we conducted separate estimations of each pathway variable. In this section, we report results for the effect of weather extremes on crop sales and tropical livestock units, and the resulting effects on HAZ, after controlling for crop yield pathway. We report results of different HAZ simultaneous estimation methods, based on the nature of pathway variables (binary for crop sales and continuous for TLU). Holding other factors constant, the CMP estimates consistently showed negative and significant effect of most extreme weather events on crop sales, only in models with separate estimation of extreme events as shown in Table 7.2 of the appendix. For models with all extreme weather events, even though the sign of effect of weather extremes was in the expected direction, the negative effect was rather insignificant as shown in column 2 of Table 2.3, except for heat wave frequency in the previous five years.

The coefficients of the 1$^{st}$ stage of Table 2.3 and Table 7.2 are not interpretable since they are based on the probit models used in CMP. Therefore, we report average marginal effects (AME) estimates of extreme weather events and other determinants of probability of crop sales, presented in Table 7.3. The corresponding AME for column 2 of Table 2.3 are presented in column 5 while columns 1 - 4 presents AME estimates of Table 7.2, of each individual extreme weather variable. Occurrence of dry spell in the previous year reduced the probability of crop sales in the previous year by 7 percentage points. The probability of market sales due to dry spell reduced to 4 percentage points, after controlling for all extreme weather events, and the effect was insignificant as shown in columns 2 and 5 of Table 7.3 respectively. Temperature extremes significantly lowered the probability of crop markets sales by up to 3 percentage points in separate estimations, and a significant 0.3 percentage points after accounting for multiple extreme weather events. Other determinants of crop sales include use of inorganic fertilizers, pesticides, improved seeds, cultivation of cash crops, and crop diversification which increased the probability of market sales by 15, 11, 7, 6 and 4 percentage points respectively as shown in Table 7.3, column 5.

Joint estimates of the effect of crop sales on HAZ, controlling for crop production are presented in column 3 of Table 2.3. Unlike crop and nutrients pathways whose coefficients on HAZ were positive, the coefficients of crop sales on child HAZ were negative and insignificant. Children in households that sold crops had lower HAZ scores of 0.114 standard deviations. Negative effect of crop sales on HAZ might imply that perhaps households used revenues from crop sales on other non-food items, as opposed to food items. This also depends on the gender of the person responsible for decision making regarding usage of income from crop sales, and how nutritious conscious they are.

Regarding livestock holdings, precipitations extremes were negatively associated with TLU as shown in Table 2.3. However, the statistical significance was only observed on the drought frequency variable in the 3SLS estimations (livestock equation), without adaptation and coping controls in the first stage.

**Table 2.3:** Effect of extreme weather events on crop production and sales, and on HAZ

| | CMP | | | 3SLS | | |
|---|---|---|---|---|---|---|
| VARIABLES | 1st stage Crop yield (t-1) | 1st stage Crop sales (t-1) | 2nd stage HAZ | 1st stage Crop yield (t-1) | 1st stage TLU (t-1) | 2nd stage HAZ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Crop yield(t-1) | | | 0.035 | | | 0.167* |
| | | | (0.061) | | | (0.096) |
| Crop sales(t-1) | | | -0.114 | | | |
| | | | (0.289) | | | |
| TLU (t-1) | | | | | | 0.155 |
| | | | | | | (0.102) |
| **Extreme weather** | | | | | | |
| Dry spell (5year) | -0.060 | 0.042 | | -0.143*** | -0.564*** | |
| | (0.042) | (0.046) | | (0.048) | (0.213) | |
| Dry spell (t-1) | -0.803*** | -0.207 | | -0.595*** | -0.191 | |
| | (0.188) | (0.196) | | (0.202) | (0.866) | |
| Heatwave (t-1) | -0.377*** | -0.047 | | -0.399*** | 0.139 | |
| | (0.050) | (0.052) | | (0.055) | (0.243) | |
| Heatwave (5year) | -0.026*** | -0.017** | | -0.024*** | 0.081** | |
| | (0.008) | (0.009) | | (0.009) | (0.039) | |
| **Adaptation strategies** | | | | | | |
| L1. Number of crops | 0.158*** | 0.219*** | 0.018 | 0.157*** | - | -0.003 |
| | (0.024) | (0.032) | (0.027) | (0.027) | - | (0.037) |
| L1. Improved seed | 0.061 | 0.360*** | 0.051 | 0.091 | - | 0.038 |
| | (0.100) | (0.129) | (0.099) | (0.114) | - | (0.102) |
| L1. Pesticides | 0.386*** | 0.581*** | -0.003 | 0.340** | - | -0.101 |
| | (0.123) | (0.200) | (0.123) | (0.144) | - | (0.135) |
| L1. Organic fertilizer | 0.357*** | 0.164 | 0.093 | 0.376*** | - | -0.049 |
| | (0.121) | (0.154) | (0.117) | (0.134) | - | (0.166) |
| Ll. Inorganic fertilizer | 0.128 | 0.786* | -0.252 | 0.162 | - | -0.296 |
| | (0.194) | (0.430) | (0.177) | (0.207) | - | (0.183) |
| L1. Water harvesting | 0.266*** | -0.035 | | 0.248** | - | |
| | (0.087) | (0.099) | | (0.098) | | |
| **Other variables** | | | | | | |
| L1. Crop area | -0.127*** | -0.001 | 0.022* | -0.129*** | - | 0.033* |
| | (0.010) | (0.012) | (0.012) | (0.011) | | (0.019) |
| L1. Cash crop | | 0.326*** | | - | - | - |
| | | (0.119) | | | | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Coping strategies | No | No | Yes | No | No | Yes |
| Constant | 5.846*** | 0.393* | -1.434** | 5.746*** | -1.246 | -1.909** |
| | (0.210) | (0.231) | (0.686) | (0.248) | (1.112) | (0.841) |
| Log likelihood | -5590 | -5590 | -5590 | | | |
| Observations | 1,615 | 1,615 | 1,615 | 1,267 | 1,267 | 1,267 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We also observed significant and negative association of dry spell in the CMP model accounting for all pathways as shown in Table 7.4. Rural families experiencing high number of drought events occurrences over the past five years had less livestock holdings as compared to those with less drought events. Specifically, an additional increase in one drought event reduced livestock holdings by about 0.38 to 0.56 units as shown in columns 5 of Table 2.3 and column 2 of Table 7.4. The fact that only the cumulative dry spell variables were significant, and negative, while the short-term variables were insignificant implied that livestock is more adaptable to short-term extreme weather events, thus does not respond to immediate changes on extreme weather events. Moreover, most rural households in districts experiencing more frequent weather extremes, tend to derive their livelihoods from livestock activities as opposed to crop related activities. Unlike its effects on crop production, heat wave event variables had positive effect on TLU. It's unclear what could be driving the positive effect.

Turning to the association between livestock and HAZ, our results report positive effects of livestock holding on HAZ. A one unit increase in prior year TLU was associated with an increase HAZ scores between 0.16 standard deviations as shown in Table 2.3. However, the effect was insignificant, even though weakly significant associations were reported in CMP model consisting of all pathways as shown in Table 7.4.

Based on our results, we conclude that as much as livestock and crop sales were negatively affected by extreme weather events to some extent, most estimates were insignificant in the respective first stages consisting of all-weather variables. Furthermore, the coefficients of crop sales were insignificant on HAZ in most estimations. Therefore, we fail to confirm the importance of crop sale mechanisms on child HAZ. On the other hand, the effect of livestock on HAZ though positive was inconsistently significant. Given that livestock is used for diverse purposes, a special focus on livestock products would provide more information, rather than livestock holding.

**Extreme weather events on child HAZ, through the disease pathways**

Controlling for WASH index, and other relevant factors, the results of probit model in the CMP simultaneous analysis for diarrhoea and fever are presented in Table 2.4. Further results on the association between diarrhoea or fever and HAZ are also reported. The corresponding model with all weather extremes for Table 2.4 is not reported because of convergence issues. However, we report model of joint estimates, including multiple pathways and extreme weather events as shown in Table 7.4. For interpretation of results, we also report the average marginal effects in Table 2.5 since the probit coefficients of extreme weather events on diarrhoea and fever probit models in Table 2.4 and 7.4 are not interpretable. The probability of diarrhoea occurrence increased significantly with increases in heat wave events and frequent drought events. A one month increase of heat wave in the prior year main season increased the probability of diarrhoea in the previous year by around 2 percentage points as shown in Table 2.5 columns 3 and 5. A smaller effect of 0.2 percentage points was observed on the cumulative five-year count variable of heat events, for separate estimations. However, after controlling for multiple weather extremes, only short-term heatwave variable in the prior year main season was significant and positive[10]. On the

[10] The coefficients for joint estimates are presented in Table A4 while all marginal effects results in Table 4.

contrary, only an increase in precipitation extreme event in the last five years had significant effects on increasing the likelihood of diarrhoea, in the separate estimations. The direction of effect was positive as expected though insignificant in models with all extreme weather events. Other determinants of child diarrhoea include child age and household head education which reduced the probability of diarrhoea. Children in the north and east regions of Uganda were more likely to have diarrhoea episodes as compared to those from central by at least 6 percentage points as shown in Table 2.5. This is expected since most of the drought's events occur in the north while most of the flood events occurs in the east region, thus compromising water quality and quantity. Better water and sanitation conditions reduced the probability of diarrhoea, especially in models with dry spell. However, the effect was insignificant.

Insignificant and mixed results were noted on the effect of weather extremes on fever. Except for heat wave event in the prior year which significantly increased the probability of fever by 3 percentage points in models with all extreme weather events. These probit coefficients estimates are presented in Tables 2.4 and 7.4 while AME in Table 2.5. Further results on determinants of fever indicate that household head education reduced likelihood of fever. Concerning the relationships between disease pathway variables and HAZ, incidence of diarrhoea was negatively associated with child HAZ scores. Children with diarrhoea in the previous year were shorter than those without diarrhoea- a difference in HAZ scores of up to -1.7 standard deviations as shown in Table 2.4. Similarly, fever occurrence led to lower children HAZ scores, with almost the same effect sizes and level of significance. The results on the effect of fever and diarrhoea on HAZ remained consistent in the joint estimation consisting of multiple weather variables, as shown in Table 7.4.

To summarize the results of the nexus between weather extremes – disease- child HAZ, we reveal that diseases led to large reductions in HAZ. However, some weather extremes did not have significant effects on the probability of disease occurrence, especially fever. Only heat wave variables and cumulative 5-year drought variables had positive and significant effects on diarrhoea, and diarrhoea in these particular estimations led to significant decreases in HAZ. Therefore, diarrhoea was a possible transmission mechanisms of extreme weather events on HAZ. Results on fever are inconclusive.

**Table 2.4**: Effect of weather extremes on diseases, and HAZ – CMP results

| VARIABLES | Diarrhoea (t-1) | Fever (t-1) | HAZ | Diarrhoea (t-1) | Fever (t-1) | HAZ | Diarrhoea (t-1) | Fever (t-1) | HAZ | Diarrhoea (t-1) | Fever (t-1) | HAZ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **Pathways** | | | | | | | | | | | | |
| Diarrhoea (t-1) | | | -1.726*** | | | -1.724*** | | | -1.672*** | | | -1.693*** |
| | | | (0.243) | | | (0.244) | | | (0.251) | | | (0.248) |
| Fever (t-1) | | | -1.822*** | | | -1.813*** | | | -1.830*** | | | -1.827*** |
| | | | (0.221) | | | (0.221) | | | (0.221) | | | (0.219) |
| **Extreme weather events** | | | | | | | | | | | | |
| Dry spell (5-year counts) | 0.054* | 0.013 | | | | | | | | | | |
| | (0.032) | (0.026) | | | | | | | | | | |
| Dry spell main season (t-1) | | | | 0.198 | 0.132 | | | | | | | |
| | | | | (0.173) | (0.132) | | | | | | | |
| Heatwave main season (t-1) | | | | | | | 0.096** | -0.007 | | | | |
| | | | | | | | (0.039) | (0.029) | | | | |
| Heatwave (5-year counts) | | | | | | | | | | 0.010** | -0.005 | |
| | | | | | | | | | | (0.005) | (0.004) | |
| Constant | -0.713 | 0.234 | 0.043 | -0.781 | 0.228 | 0.034 | -0.849 | 0.231 | 0.034 | -0.762 | 0.224 | 0.025 |
| | (0.527) | (0.379) | (0.662) | (0.526) | (0.379) | (0.661) | (0.528) | (0.379) | (0.663) | (0.527) | (0.378) | (0.662) |
| atanhrho_12 | | | 0.556*** | | | 0.553*** | | | 0.531*** | | | 0.541*** |
| | | | (0.102) | | | (0.102) | | | (0.103) | | | (0.103) |
| atanhrho_13 | | | 0.766*** | | | 0.761*** | | | 0.772*** | | | 0.769*** |
| | | | (0.107) | | | (0.106) | | | (0.107) | | | (0.105) |
| atanhrho_23 | | | 0.061 | | | 0.055 | | | 0.052 | | | 0.059 |
| | | | (0.052) | | | (0.052) | | | (0.051) | | | (0.051) |
| Log likelihood | -4183 | -4183 | -4183 | -4183.6 | -4183.6 | -4183.6 | -4181 | -4181 | -4181 | -4182 | -4182 | -4182 |
| Other covariates | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

All the covariates are first lags. Variables in the disease equations are shown in Table 2.5. HAZ equations consists of a wide range of covariates including household factors such as asset index, household head, mother and child characteristics. All the variables in the reduced form equations were lags. In the structural equation, only child characteristics were not lagged

**Table 2.5**: AME of determinants of fever and diarrhoea.

| Variables | L1. Diarrhoea (dy/dx) | | | | | L1. Fever (dy/dx) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Dry spell (5-year counts) | 0.010* | | | | 0.001 | 0.005 | | | | 0.006 (0.013) |
| | (0.006) | | | | (0.008) | (0.009) | | | | |
| Dry spell main season (t-1) | | 0.035 | | | -0.001 | | 0.048 | | | 0.049 |
| | | (0.031) | | | (0.035) | | (0.047) | | | (0.054) |
| Heatwave main season (t-1) | | | 0.017** | | 0.019** | | | -0.002 | | 0.031** |
| | | | (0.007) | | (0.009) | | | (0.010 | | (0.015) |
| Heatwave main season (5 year) | | | | 0.002** | 0.001 | | | | -0.0018 | -0.004* |
| | | | | (0.001) | (0.001) | | | | (0.001) | (0.002) |
| Child age | -0.007** | -0.007** | -0.007** | -0.007** | -0.007** | -0.003 | -0.003 | -0.003 | -0.003 | -0.004 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Child age squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Child sex | 0.006 | 0.007 | 0.006 | 0.005 | 0.002 | -0.006 | -0.005 | -0.005 | -0.005 | -0.008 |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| Household head education | -0.004 | -0.004* | -0.004* | -0.004* | -0.004* | -0.008** | -0.008** | -0.008** | -0.008** | -0.009** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Maternal/female education | 0.027 | 0.031 | 0.032 | 0.029 | 0.028 | -0.051 | -0.050 | -0.050 | -0.048 | -0.059* |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.021) | (0.033) | (0.033) | (0.033) | (0.033) | (0.033) |
| Mother age | 0.003 | 0.004 | 0.004 | 0.003 | 0.004 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Mother age squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Household head sex | 0.011 | 0.007 | 0.012 | 0.014 | 0.012 | -0.015 | -0.017 | -0.016 | -0.021 | -0.025 |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.024) | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) |
| Household head age | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |

| | L1. Diarrhoea (dy/dx) | | | | | L1. Fever (dy/dx) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Sequential (b. 2) | | | | | | | | | | |
| 3 | -0.010 | -0.005 | 0.008 | -0.012 | 0.008 | -0.095*** | -0.089*** | -0.097*** | -0.093*** | -0.061** |
| | (0.017) | (0.017) | (0.018) | (0.017) | (0.020) | (0.025) | (0.026) | (0.027) | (0.025) | (0.030) |
| 4 | -0.031 | -0.024 | -0.019 | -0.030 | -0.020 | -0.095*** | -0.089*** | -0.096*** | -0.093*** | -0.066* |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.021) | (0.032) | (0.033) | (0.033) | (0.032) | (0.035) |
| Region (base: Central) | | | | | | | | | | |
| Eastern | 0.074*** | 0.070*** | 0.065*** | 0.065*** | 0.072*** | 0.053 | 0.051 | 0.052 | 0.056 | 0.076** |
| | (0.023) | (0.022) | (0.023) | (0.022) | (0.024) | (0.036) | (0.036) | (0.036) | (0.036) | (0.038) |
| Northern | 0.086*** | 0.085*** | 0.068*** | 0.079*** | 0.067*** | 0.016 | 0.012 | 0.019 | 0.027 | 0.014 |
| | (0.023) | (0.023) | (0.024) | (0.023) | (0.024) | (0.035) | (0.036) | (0.038) | (0.036) | (0.039) |
| Western | 0.030 | 0.027 | 0.035 | 0.033 | 0.043* | -0.094** | -0.102*** | -0.092** | -0.091** | -0.080** |
| | (0.023) | (0.023) | (0.024) | (0.024) | (0.026) | (0.0370 | (0.038) | (0.037) | (0.037) | (0.039) |
| WASH | -0.002 | -0.003 | 0.000 | -0.001 | 0.004 | -0.010 | -0.010 | -0.010 | -0.011 | -0.001 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Observations | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 | 1,677 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Note: All the covariates are first lags

**Effect of extreme weather events on WAZ and WHZ through the nutrients and crop productivity pathways**

This sub-section reports results of the effects of extreme weather events on crop pathway variables in the first stage, and the effect of the respective pathways on WAZ/WHZ in the second stage. Since both child health measures respond to short-term nutrition changes and shocks, lagged covariates are not used in WAZ and WHZ simultaneous equations. Therefore, we discuss results of both measures together, despite being estimated differently. All covariates in the previously reported HAZ models were considered. However, we report and discuss only the main variables of interest in the two stages. As a starting point, we present results of the separate estimations of the different extreme events on one pathway variable (crop yield or nutrients) on WAZ as shown in Table 7.5. Dry spell in the main season reduced calorie supply by 51%, while the effect on protein and zinc was 20% and 12% respectively. The magnitude of effect of dry spell on crop yield was high, with an occurrence of dry spell in the main season lowering crop yields by 85%. An additional increase in dry spell event over the last five year also reduced the supply of all nutrients and crop yield, including vitamin A production. Similar results were also observed on the cumulative heatwave, over the last five years. The coefficients of droughts and heatwave in the main season on vitamin A were positive and significant. Similar results in terms of significance levels and coefficients signs were reported on first stage estimates of extreme weather events on WHZ as shown Table 7.6. The difference in coefficients sizes were negligible. Based on the F-statistics, it was evident that extreme weather events were strong instruments for all nutrient pathways as well as crop productivity, thus relevant for impact estimation on WAZ and WHZ.

In the second stage estimations, positive and significant coefficients of the pathways were observed in most estimations as shown in columns 2, 4, 6, 8 and 10 of Tables 7.5 and 7.6. The effect size was higher for zinc where a 10% increase in zinc led to an increase in WAZ and WHZ of approximately 0.08 standard deviations. Furthermore, a positive and significant effect of vitamin A production was reported. On average, an increase in vitamin A by 10 percent increased WAZ and WHZ significantly by 0.028 and 0.026 respectively. The magnitude of effect was almost similar to the effect of crop yield ranging between 0.019 – 0.029 standard deviations. A 10 percent increase in macronutrients increased WAZ and WHZ scores in a range between 0.028 to 0.053 standard deviations. These results indicate that both macro and micro nutrients availability matter for better child WAZ and WHZ.

For subsample analysis, all nutrients significantly influenced WAZ and WHZ of both girls and boys. However, the magnitude of coefficients was higher in girls than boys, especially in WHZ models as shown in Table 7.7 in columns 6 to 10.

We controlled for adaptation strategies and coping strategies in the respective models. However, since our main interest is on the coefficients of interactions between extreme weather events and adaptation, we rely on the estimates in Table 7.8 and 7.9. These tables show the interactions[11] of farm practices and adaptations with different weather extremes in crop production equations of both WAZ and WHZ systems of equations. Generally, the coefficients of interaction terms of water harvesting technologies and organic fertilizers were positive and significant in most regression. Coefficients of crop diversification and pesticides interactions were also positive and significant when interacted with temperature extremes variables as shown in columns 7 and 10. Similar results are reported for improved seed. These results indicate the importance of adaptation strategies in increasing crop output in the presence of weather extremes.

**Extreme weather events on WAZ and WHZ, through crop sales and livestock channels**

Estimates of the simultaneous equations consisting of two pathway variables, crop yield and crop sales on WAZ are presented in Tables 7.8, while the estimates for WHZ models are presented in Table 7.9 in the appendix. We discuss results of the crop sales model because this is of our interest. The estimates are consistent with the previously reported results, where extreme weather events led to reduced likelihood of crop sales. Probit coefficients are not interpretable, therefore, we only comment on the sign and significance levels. Children in households experiencing temperature extremes in the immediate season and over the past five years were less likely to sell crops. Similar significant results are reported on main season dry spell events. However, the effect of the cumulative five-year extreme dry spell was insignificant in both WAZ and WHZ systems. All adaptation strategies increased the probability of crop sales[12], with insignificant effects recorded only on organic fertilizers use. Heterogeneous effects of crop sales were observed on WAZ and WHZ. Participation in crop sales reduced WAZ by about 0.1 standard deviations as shown in Table 7.8, and increased WHZ by up to 0.2 standard deviations as shown in Table 7.9. However, these effects were insignificant in all models.

[11] We are unable to do interactions in the HAZ equation since we use the lags operator

[12] These results are not reported in Table 7

Relationship between extreme weather events and livestock holding, controlling for crop yield pathways are presented in Table 7.10. Only the five-year dry spell count variable significantly reduced the TLU. These results remained consistent in all regressions with a decrease in TLU in the range of -0.3 to -0.4 livestock units. We also found a positive and significant effect of TLU on WAZ and WHZ. More specifically, one unit increase in livestock holding increased children WAZ and WHZ by 0.3 and to 0.2 standard deviations respectively. The effect of extreme weather events on crop yields, and WAZ remained significant as reported in earlier models.

**Effect of extreme weather events on disease, and WAZ/WHZ**

For separate regressions of the specific extreme weather events on disease environment, in the WAZ simultaneous equations, all the weather variables significantly increased the probability of diarrhoea, except dry spell dummy variable for the main season. The rest of the variables were statistically significant at 1% level as shown in Table 7.11. Nonetheless, the significant effects on the different coefficients diminished when all the weather extremes were controlled for in one regression as shown in Table 7.13 column 1. Only heat wave five-year count variable remained statistically significant. With regards to the associations between diarrhoea and WAZ, the results showed expected significant and negative effects of increased disease incidence on child WAZ. Children experiencing diarrhoea episodes had lower WAZ scores – a difference of at least -0.4 standard deviations when compared with children who did not report any symptoms of diarrhoea. For WHZ, the coefficients of diarrhoea, though negative remained consistently insignificant as shown in Table 7.12 and Table 7.13. Focusing on extreme weather events and fever, the five-year temperature variable increased the likelihood of fever, only after controlling for all extreme weather events as shown in column 2 of Table 7.13. On the contrary, drought frequency over the past five years reduced the probability of fever in both separate and all estimates. Effect of temperature on increased probability of fever could be due to the modifying effects of temperature on geographical range of vectors responsible for vector-borne diseases, associated with fever symptoms such as malaria. The relationship between temperature and malaria is well documented in literature. Even though the effects of fever on WAZ and WHZ were significant in most estimations, the signs on the coefficients were rather mixed. Therefore, we fail to confirm fever as a possible pathway. Diarrhoea is the main pathway because incidence of diarrhoea consistently resulted to lower and significant WAZ scores, and extreme weather events increased the probability of diarrhoea.

## Road infrastructure and transport services

Given the importance of road infrastructure on market access, trade, and its sensitivity to weather extremes, we graphically explore the impact of damaged infrastructure on child undernutrition using subjective responses. In the UNPS[13] respondents were asked if they had access to different types of roads within the community, and if the roads were usable throughout the year. One of the reasons why the specific roads were unusable was bad weather. Results in Figure 2.6(a) reveal that children in households residing in locations where roads were affected by bad weather had lower scores over the years. In fact, while children in households with good roads registered improvement in the HAZ over the years, those affected recorded a decline in HAZ. Similar reduction trends were observed on WAZ and WHZ for those children in locations where roads were affected by bad weather as shown in Figure 2.6b and 2.6c respectively.

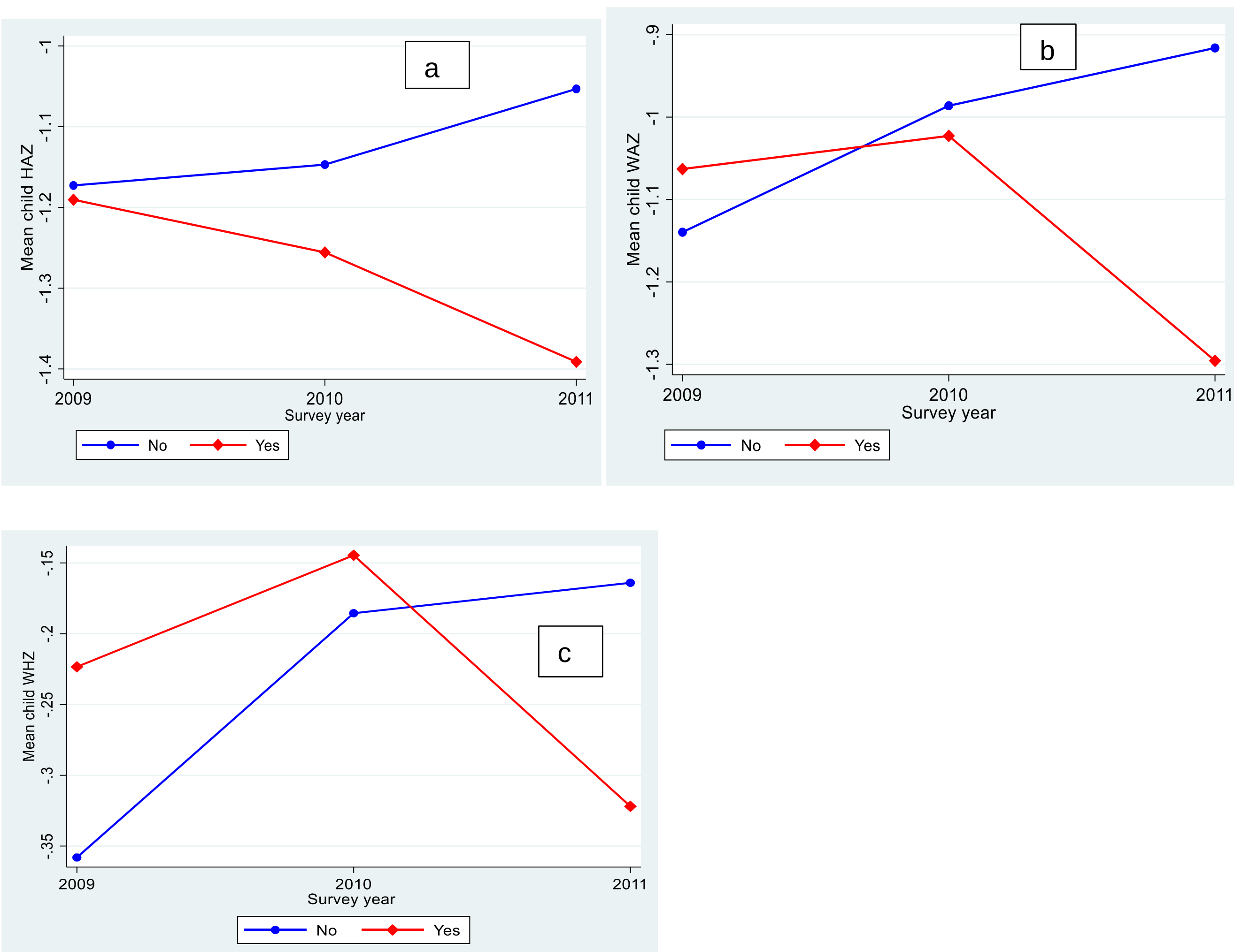


**Figure 2.6:** Relationship between unusable road due to weather extremes and undernutrition HAZ (a), WAZ (b) and WHZ (c)

[13] Is the road usable all the year round? Why was the road unusable? (Bad weather= Yes). Other reasons for unusable roads such as: Bad terrain, Potholes, Poor drainage, Bushy roads, Insecurity and others are in the No category. We also include usable road in the No category. This information was not collected in 2013/2014 wave.

## 2.5 Discussions, conclusion and limitations of the study

### Discussion

Child anthropometry indicators reflects the general health of children, dietary adequacy and are further used for tracking child growth and development tends overtime (Fryar et al., 2016). Child health is affected by weather extremes through different mechanisms. However, rigorous empirical analyses of causal pathways are missing. We address this gap considering all the undernutrition measures. Overall, the results showed negative effects of extreme dry spells on macronutrients, minerals, vitamins and crop productivity in the first stage. Furthermore, we found positive impacts of selected nutrients and crop productivity on child HAZ, WAZ and WHZ, in the second stage. Our findings on the negative associations of extreme weather events on food nutrients are consistent with other previous empirical studies (Antonelli et al., 2020; Arlappa et al., 2011; Carpena, 2019; Fischer et al., 2019). From the production side, Fischer et al. (2019) experimental study found out that severe droughts decreased nutrient concentrations in most food parts of the crop in Kenya and Uganda. In particular, negative and significant associations were found between droughts and zinc concentration in food crops. However, they also found positive associations between mild drought and some nutrient concentrations in food crops (Fischer et al., 2019).

Focusing on nutrient consumption, Antonelli et al. (2020) and Carpena (2019) reported that long-term weather events had negative effects on calorie consumption. The latter study also reported a decrease in protein intake in Indian diets because of dry shocks. Similarly, Arlappa et al. (2011) found out that during drought conditions, vitamin A dietary intake was lower and below the recommended intake, especially among rural children in India. Another study conducted by Singh et al. (2006) revealed that droughts increased prevalence of protein-energy malnutrition (PEM), and protein and calorie deficiencies in the diets of Indians. Additionally, Amondo et al. (2019) found out that occurrence dry spell reduced crop yields, especially among the non-adopters of drought-tolerant varieties in Zambia while Carpena (2018) reported negative associations of droughts and crop yield in India.

The results on the negative effect of temperature extremes on crop yields are consistent with Hu and Li (2019); Letta et al. (2018) who documented the adverse effects of high temperatures on crops yields. Heat stress is one of the major limiting factors in crop production. Siebert and Ewert (2014) argued that high temperatures results into seed abortion, leaf senescence due to decreased photosynthesis, low pollen production and viability thus low production. The findings on extreme weather events implies that high temperatures and lack of enough rainfall are detrimental to crop growth and development, especially during the planting and growing periods, with negative effects on both quality and quantity of crops. High rainfall in absence of floods therefore, translates into availability of abundance and food varieties for households, thus good nutritional status. This is evidenced by the positive direct link between nutrients supply and crop productivity on child HAZ. Strong evidence on the relationship between zinc deficiency and growth faltering especially in children has been previously reported (Brown et al., 2002; Rivera et al., 2003), while vitamin A resulted into stunting, only when the deficiencies were severe (Rivera et al., 2003).

On crop sales, even though extreme weather events significantly reduced the probability of market sales, we found insignificant negative effects of crop sales on children HAZ, WAZ and WHZ. These results are consistent with Kirk et al. (2018) who presented a negative relationship between agricultural income and nutrition. Nonetheless, the results are in contrast with Koppmair et al. (2017) who reported a positive and significant association between the share of food crop sold and diet diversity at both individual and household levels. Additionally, Carletto et al. (2017) reported positive and non-significant effects of commercialization on children HAZ, WAZ and WHZ. In our study, it seems that revenues from crop sales were not sufficient enough to improve child nutrition significantly or used on other purchases apart from food items. Alternatively, it might be possible that most household participating in market sales were specializing in food crops, especially staples which are sold at lower prices with sales made immediately after the harvest as opposed to cash crops as argued by Carletto et al. (2017).

On livestock, counts of dry spell events had a negative effect on TLU. However, there was no significant effect on dry spell dummy coefficient. The results on dry spell dummy are consistent with Hoddinott and Kinsey (2001) who reported that livestock holdings were not affected by a drought occurrence, but rather, livestock was used as a principal coping strategy to drought. The result on the positive effect of heat on livestock are however in contrast with Letta et al. (2018) who found insignificant effect of temperature shocks on TLU. Sejian et al. (2015) indicates that animals are more adaptable to hot weather and climates, thus the direct effect of heat can be observed through milk and meat production. The insignificant associations observed between livestock units and HAZ are partly consistent with Azzarri et al. (2015) who reported that livestock in Uganda did not have significant effect on child stunting. However, Hoddinott and Kinsey (2001) found a positive impact of livestock holdings on child height growth rates in Zimbabwe. Additionally, Kabunga et al. (2017) reported that probability of child stunting was lower in households that adopted improved daily cows in Uganda. Positive and significant association between TLU and WHZ or WHZ reported in this study is consistent with Azzarri et al. (2015) who despite reporting no association with HAZ, found decreased probability of wasting and underweight in children residing in households owning small ruminants.

The positive effects of precipitation and temperature extremes on probability of diarrhoea are consistent with other previous studies. For example, Akil et al. (2014) noted that *Salmonella* and *Vibrio cholera*, which are some of the food and waterborne pathogens responsible for diarrhoea infections were positively correlated with high temperatures. Additionally, bacterial pathogens like *Escherichia coli* e.t.c linked with diarrhoea were found to be associated with high temperatures which facilitates faster replication and survival extension in external environment (Azage et al., 2017). Emont et al. (2017) and Bandyopadhyay et al. (2012) reported increased diarrhoea risk during drought periods because of water shortages and compromised quality of drinking water. Furthermore, Epstein et al. (2020) found out that low annual rainfall in Uganda had significant and harmful effects on child diarrhoea. Increase in probability of diarrhoea in turn affected child undernutrition status since we found a negative association between diarrhoea and HAZ or WAZ. The results are consistent with Richard et al. (2013), who reported significant and negative cumulative association of diarrhoea with child height/length . The same study also found significant associations between lower child weight with diarrhoea burden during the 30 days prior to the interview.

Lastly, the positive effect of high temperatures and probability of fever are consistent with Texier et al. (2013) who found a positive association between risk of malaria and time spent in areas with high temperature. The negative effects of droughts on fever, especially in the WAZ and WHZ equations, where statistical significance was reported is in contrast with Epstein et al. (2020) who reported that low annual rainfall trends in Uganda had deleterious effects on fever. Our findings on the association between fever and undernutrition were mixed. However, given the negative and significant coefficients in most second stage estimations, we conclude that the results were consistent with Gone et al. (2017) study which indicated that malaria in early years of childhood years may lead to lasting undernutrition and long-term health.

The research findings indicate that weather extremes led to substantial food production losses and negative health impacts. However, the extent to which these negative effects are realized is dependent on implementation of effective adaptation and coping interventions in a timely manner. The adaptation concept has increasingly received attention and is a focal point in most climate policy implementations and negotiations (Smith et al., 2014; Woodward et al., 2014) given that the execution of mitigation strategies has been on a slow pace. Households implemented different adaptation and coping strategies in response to extreme weather events. Most of the adopted adaptation strategies led to increased nutrients and crop production with significant effects observed on water harvesting, crop diversification, improved seed, pesticide and organic fertilizers. Similar findings were reported by Asfaw et al. (2015) on sustainable land management practices and Makate et al. (2016) on crop diversification. Furthermore, agricultural diversity on farm translates into household dietary diversity (Koppmair et al., 2017). The results of the positive and significant effect of nonfarm work is consistent with Cunguara et al. (2011) who argued that during drought years, households were involved more in non-farm activities. We found positive and significant effect of credit access on crop production, while the effect on WAZ and HAZ was positive and insignificant. These results are partly consistent with Asfaw et al. (2015) who reported that credit access enabled households to cope with the negative weather effects on food expenditures.

Government aid was positively associated with child HAZ though insignificant, while effects of informal safety was negative and insignificant. These results are in contrast with Groppo and Kraehnert (2016) who reported that emergency food aid and assistance from relatives and friends was significantly and positively associated with HAZ of children exposed to weather extremes. Finally, good infrastructure enables access to both output and input markets, thus plays an important role in dietary diversity (Koppmair et al., 2017). Extreme weather events such as floods may damage infrastructure thereby inhibiting market access and has an effect on food, feed and input prices. Food might be unavailable or accessed at high costs when infrastructure is damaged, thus low child nutritional status. Our results support this argument since children residing in areas with damaged infrastructure because of bad weather had lower nutritional status as evidenced by low HAZ, WAZ and WHZ. Furthermore, market access led to higher production of nutrients and crop production.

## Conclusion and limitations of the study

Deficiencies of macronutrients and micronutrients at early stages of life might have long term effect on individuals. The study investigated the indirect effect of extreme weather events on children nutritional health outcomes exploring the different causal mechanisms, using simultaneous equations methods. Child health outcomes were measured by HAZ, WAZ and WHZ. Uganda National Panel Survey was used in combination with objective gridded long-term rainfall and temperature, CHIRPS and MODIS products respectively. We find significant and negative effects of extreme weather events on calorie, protein, zinc and vitamin A availability as well as crop yield. Increased production of these nutrients significantly led to better HAZ, WAZ and WHZ. Additionally, livestock holding was positively associated with WAZ and WHZ, at least at 5% significance level, and not HAZ.

While extreme weather events such as heatwaves increased the probability of diarrhoea and fever, occurrence of child diarrhoea had negative and significant effects on HAZ, WAZ and not WHZ. On the other hand, the effect of extreme weather events on fever was insignificant in most estimations while the association between fever and undernutrition was significant and mixed. We also observe negative and insignificant effects of crop sales on HAZ, WAZ and WHZ. Taking into consideration first and second stage estimations, we fail to confirm crop sales and fever as possible pathways through which extreme weather affect undernutrition. We therefore conclude that crop productivity, micro and micronutrients availability and livestock holding were the main agricultural mechanism, with the latter being important for weight measures. Besides, diarrhoea pathway was an important pathway for child HAZ and WAZ.

The results further showed that coping strategies such as precautionary savings, credit access and nonfarm work were associated with better HAZ scores, while involuntary change of diet had negative effects on HAZ. Households involved in good agronomic practices such crop diversification, pesticide use, organic fertilizers and improved seed registered higher crop and nutrient production despite the extreme weather events. Furthermore, access to markets and good road networks matter for improved crop production as well as better child health. These results indicate that right adaptation strategies have the capacity to increase crop and nutrient production, and indirectly minimize health effects resulting from extreme weather events. Therefore, rural households should be sensitized of the same. Furthermore, policy makers should advocate for the right approaches - ex-ante or anticipatory based measures that improve crop and nutrition and protect households from other climate related health risks given future projections of increasing climate extreme events. Investment in child-centred approaches will surely pay off now, and in the future.

Future studies should consider more long-term socio-economic panels and up-to date data in the analysis, and further experimental analysis. Our study had the following limitations: First, considering that the secondary household data was collected for other purposes other than our research objectives, some key variables were lacking on certain age groups, thus, not included in the regressions. For instance, information on breastfeeding, complementary feeding of all children, mother health endowment, households' access to nutritional information and health insurance. Second, even though the weather products provided long-term information on rainfall and temperature, the household surveys were a short-run five-year panel, and anthropometrics not collected for children beyond the age of five thus limiting study of long-term effects of weather effects on the different outcomes.

# Chapter 3: Health gender gap in Uganda: Does weather effects play a role?

## 3.1 Introduction

Health and gender equality are both fundamental human rights enshrined in SDGs, with synergies between them. While health is recognized as an asset that fosters economic growth and development (Bloom et al., 2019; Gallup & Sachs, 2001; Schultz, 2010), and enhances coping ability and resilience (World Health Organization, 2014). Gender equality is not only a key determinant of health (Commission on Social Determinants of Health, 2008; Shannon et al., 2019), but also facilitates economic growth and development (Shannon et al., 2019; World Bank, 2011), improved nutrition and food security (Agarwal, 2018; Meinzen-Dick et al., 2012), lowers fertility and child mortality (Shannon et al., 2019). At the intersection of gender and health is access to safe and sufficient water, which is also a fundamental human right (World Health Organization & United Nations Children's Fund, 2017).

Currently nearly half of the world population experience physical water scarcity for a minimum of one month in a year (Boretti & Rosa, 2019) and 1.6 billion people experience economic water scarcity (The United Nations World Water Development Report, 2021). There exist global inequalities in access to safe water drinking water translating into health inequalities. For instance, in developing counties, lack of access to sufficient and safe water is among the three most important factors for poor health (Geere et al., 2010), yet an estimated 400 million people in sub-Saharan Africa (SSA) have limited access to basic drinking water (Mason et al., 2019; United Nations Children's Fund & World Health Organization, 2019). Apart from health, water scarcity has severe economic consequences. Therefore, improvements in water security has both health and economic benefits. For instance Prüss-Üstün et al. (2008) estimates that while improvements in water, sanitation and hygiene (WASH) conditions could prevent about 10% of the total disease burden globally, investments in WASH can improve productive days and school attendance by additional gains of about 320 million and 272 million days per year respectively, and further time savings.

Water availability and other determinants of health are threatened by weather variability and changing climatic conditions. For instance, the proportion of people facing water insecurity is projected to increase in the near future due to climate change (The United Nations World Water Development Report, 2021; United Nations Children's Fund, 2021). This implies more health risks in future, especially in developing countries which have least adaptive capacities, weak health systems and where restrictive gender norms are predominant. Weather events and changing climatic conditions are increasingly recognized as "gender-based health inequality risk-multipliers" exacerbating the already existing gender differentials in health risks (Sorensen et al., 2018; van Daalen et al., 2020; World Health Organization, 2014) .

Therefore, in understanding the complex linkages between weather or climate events and gender differentiated health outcomes, it's important to first highlight the general pathways through which gender and associated inequalities are translated into health risks, and the existing health inequalities among men and women. These pathways include differential susceptibility and exposures to injuries, diseases and disabilities (Shannon et al., 2019; Vlassoff, 2007). Besides, differences in health behaviours and response of health systems to gender in terms of health care, financing and division of labour (Gupta et al., 2019; Manandhar et al., 2018; Shannon et al., 2019) constitute other pathways. The above mentioned are attributed to discriminatory values, beliefs, restrictive gender norms and roles (Gupta et al., 2019; Shannon et al., 2019), which further leads to discriminations in access to resources (Neumayer & Plümper, 2007), which might disadvantage one sex leading to "a group-level gender effect" or individual health inequalities (Phillips, 2008). Gupta et al. (2019) argued that gender norms in particular have contributed to the current failure of developing nations health sectors to address some important health challenges such as high maternal mortality rates.

Gender roles also contribute to the disparities in health among men and women (Ballantyne, 1999; King et al., 2018; Macintyre et al., 1996). For instance, the multiple roles in productive work and caregiving for women significantly burden them, and may contribute to high levels of anxiety, stress (Ballantyne, 1999; Shannon et al., 2019), and subsequent infections for highly infectious diseases (World Health Organization, 2014). Furthermore, more involvement of women in reproductive or domestic roles rather than productive or paid work makes them to have less autonomy, low social status in the society, thus unable to afford better health care services (Vlassoff, 2007). Due to lack of resources, women may opt for informal health care services, unless men finance their treatment and transport costs (Heise et al., 2019). On the other hand, men have fewer caring roles, enjoy economic independence and decision-making power (King et al., 2018; Vlassoff, 2007). However, the socially prescribed roles of men as breadwinners can potentially lead to increased anxiety and stress levels (Shannon et al., 2019) and the risk of infection of diseases depending on their work environments (Vlassoff, 2007). Additionally, men are more involved in risk-taking roles and harmful health behaviours dictated by sociocultural norms, and associated with masculinity, therefore, they experience high mortality risks (King et al., 2018; Manandhar et al., 2018).

Both sex and gender matter in understanding illnesses and other health outcomes, and therefore important in design and implementation of health policies (Leung et al., 2004; Vlassoff, 2007). Currently there exists gender gap in longevity, where women live longer today than men in most countries across the world (Harder & Sumerau, 2018; Zarulli et al., 2018). However, women also exhibit poorer health than men since they have high morbidity rates mainly from nonfatal illnesses, disabilities and reduced quality of life in old age (Bird & Rieker, 2008; Harder & Sumerau, 2018). Scientific consensus exists that these health disparities between women and men are not entirely biological and gender inequalities have a role to play (Neumayer & Plümper, 2007; Schünemann et al., 2017; World Health Organization, 2014). For instance, the longevity disadvantage in men is mostly associated with harmful health behaviours (King et al., 2018) and occupational choices (Felder, 2006). Moreover, Luy and Wegner-Siegmundt (2015) stated that women in developed countries live longer today because of changes in non-biological factors and behaviours. In some societies, women also engage more in preventive health behaviours and have a high health literacy than men (Gyasi et al., 2019). Therefore, most gendered health inequalities are avoidable, if proper actions are taken (Kennedy et al., 2020; King et al., 2018).

Focusing on climate, literature reveal that men and women are affected differently by disasters, and women life expectancy advantage is likely to be narrowed by natural disasters, especially where women have low socio-economic status (Neumayer & Plümper, 2007; World Health Organization, 2014).

Furthermore, women are affected more by other climate related health outcomes such as infectious diseases and malnutrition as compared to men (Preet et al., 2010; World Health Organization, 2014). Other health risks associated with climate events include heat stress, mental stress, respiratory illnesses and extreme weather events which are more pronounced on people working outdoors, rural residents and people with low socio-economic, cultural and political status (Global Gender and Climate Alliance, 2016; Yusa et al., 2015).

Exposure, sensitivity and adaptive capacity are the three main factors that determine vulnerability to climate impacts among individuals and households (Cardona et al., 2012), and this is also true for health impacts as earlier outlined. With regards to exposure, gender roles determine how and where women and men spend most of their times, thus a major determinant of the different exposure and intensity patterns to the infectious agents of the diseases (Rancourt, 2013; World Health Organization, 2007). For instance, men usually spent most of their time conducting outdoor activities, and in locations that are far from their homes, thus exposed to infectious agents outside and far from home environments. Similarly, women in SSA, especially in rural areas are mostly engaged in agricultural production and provide more agricultural labour than men, therefore spent most of the time outdoors (Doss, 2001, 2018). Furthermore, their caregiving roles and workloads are increased with extreme weather events as a result of increased illness of other household members (especially children), increased demand for water during drought conditions and also difficulties in accessing food and water for the household.

Women and girls in most rural areas are responsible for water collection activities (Graham et al., 2016; Sorensen et al., 2018), and suffer more during periods of water scarcity caused by drought or shifting rainfall patterns (World Health Organization, 2014). These meteorological conditions limit water access making individuals responsible for water collection to travel more distance to water collection points or increase time spent in water collection activities beyond 30 minutes for round trip, which is above the WHO/UNICEF JMP cut off points for basic water access (World Health Organization & United Nations Children's Fund, 2017). Apart from increasing vulnerability to stress, anxiety, exposure to other diseases (Preet et al., 2010), more time spent on water collection and other gender roles lead to the possibility of women neglecting their health care needs (Whittenbury, 2013). Furthermore, they limit access to health-related inputs such as education, labour income and other livelihood opportunities (World Health Organization, 2014) which further hinder adaptation and general response to illness, thus *exacerbating* women vulnerability to other climate sensitive or other health outcomes. Because of limited access to resources, women with low socio-economic also have a tendency of prioritizing their resources on other family's needs at the expense of their own health (World Health Organization, 2007).

In view of the above discussions, analyses in this paper focus on linkages between climate variability and health outcomes with a gender perspective, using sex disaggregated data. To our knowledge, until now there exist inadequate empirical evidence on the effects of climate variability on the health of the working age men and women, the indirect effect of weather events through water collection time pathway, gender health gap and the magnitude of the contribution of weather variables and health seeking behaviours to the gender health gap in the Ugandan context. Therefore, our study seeks to fill this gap by combining objective weather data and nationally representative socio-economic dataset to address the following research questions; (1) What is the effect of temperature and rainfall variability on health outcomes of men and women in the working age group? (2) Is the association between weather variability and illness among men and women mediated by water collection time? (3) What is the association between healthcare services and health outcomes among men and women? (4) What is the contribution of weather variability and health care services in explaining the gender gap in health outcomes? The hypothesis are as follows; (1) Increase in weather variability will lead to increased likelihood and days of illnesses in women of the working age than in men. (2) The positive effect of weather variability on probability of illness in women will be fully mediated by an increase water collection time. (3) Health care services will explain a higher portion of the gender gap in the number of sick days and number of days of restricted work.

The rest of the paper is organized as follows; the next section 3.2 reviews the existing literature and presents the theoretical framework and conceptual framework. The methodology (data sources and empirical strategy) is outlined in section 3.3 and section 3.4 presents the descriptive statistics and empirical findings. Section 3.5 presents the discussion and conclusion.

## 3.2 Literature review, theoretical and conceptual frameworks

### Literature review

This study builds on, and merges two diverse research strands of literature in order to assess the gender differentiated impacts of weather anomalies on health, and further the contribution of these variables to the total observed health inequalities among men and women. The first stand of literature focuses on the effects of extreme weather events, climate variability or climate change on health among males and females of the different age groups. Several studies mainly in epidemiological, environmental and social science fields have attempted to examine this relationship, especially in the developed countries, because of accessibility of relevant data (Campbell et al., 2018). Focusing on health impacts of heat waves on mortality and morbidity, including mental health in several countries, Bogdanović et al. (2013); D'Ippoliti et al. (2010); van Steen et al. (2019) studies find that elderly women, especially beyond the age of 75, were at a higher risk of heat related mortalities than men (van Steen et al., 2019), with up to two times more mortalities in women than in men (Bogdanović et al., 2013).

On the other hand, greater risks of mortalities from heat waves were reported among unmarried men than unmarried women (van Daalen et al., 2020). Correspondingly, Badoux et al. (2016) ; Lowe et al. (2013); Salvati et al. (2018) studies reveal that more males of different age-groups were killed or experienced greater risks of mortalities from extreme events, such as, floods and landslides or avalanche than females in different developed countries. The latter study however reports that females experienced high risks of physical and psychological health effects than men. Similarly, Whittenbury (2013) finds that rural women health was affected by droughts because of increased time and financial demands, marital breakdowns, separation and increased incidence of violence against women. Using historical data, Zarulli et al. (2018) reveal that during periods of famine caused by extreme weather events, women in most age groups survived better and had higher mean life expectancies than men. Furthermore, increased suicide cases were reported in male farmers as compared to women during drought years (Hanigan et al., 2018), and women cognitive performance was better than men under high temperatures (Chang and Kajackaite (2019).

In developing countries, despite future projections of increased health impacts due to climate change given the countries geographical locations, weak health system and lack of resources to adapt, there has been limited research in the past on general health effects of climate events (Liang & Gong, 2017; Rataj et al., 2016), and gender differentiated health- impacts in particular. Most of the infectious diseases are climate sensitive and contribute significantly to the total burden of the disease in developing countries. Malaria is one of the diseases in developing countries whose increased incidence, cases and mortalities have been attributed to climate change and weather anomalies (Caminade et al., 2014; Colón-González et al., 2016; Sewe et al., 2016; Tompkins et al., 2019). The risk of malaria is known to be higher in women, especially the pregnant women whose immunity to the disease is weakened, and can result to maternal illnesses, preterm birth or low child weight (Pradhan & Meherda, 2019). Apart from pregnant women, women are generally vulnerable to a high risk of malaria due to their assigned responsibilities in household and agricultural fields (Woldu & Haile, 2015) and exposure to unprotected water sources and poor housing conditions (Ayele et al., 2012).

Substantial literature reveals that diarrhoea and cholera are positively associated with extreme weather events and climatic changes (Bwire et al., 2016; Kolstad & Johansson, 2011; Moors et al., 2013). Even though males are at high risk of diarrhoea in childhood due to biological reasons, Bwire et al. (2016), United Nations Children's Fund (2010) and World Health Organization (2007), point out that the trend of diarrhoea and other infectious diseases changes among adults with females recording higher rates because of gender norms and roles (United Nations Children's Fund 2010). For instance, vulnerability of female to diarrhoea in adulthood is due to increased exposure given women's responsibilities in responding and preventing the disease, and exposure to contaminated water sources (United Nations Children's Fund 2010). Other previous studies focusing on drought health effects, argue that women as custodians of water collection, experience acute labour burdens during periods of water shortages because of carrying water over long distances which have health implications (Alpino et al., 2016; Nellemann et al., 2011). Focusing on high temperature, Egondi et al. (2012) report that child mortalities and non-communicable diseases (NCD) were linked with the rising temperatures, while acute infections were associated with low temperatures, causing more deaths in males aged over 50 years. Female died more from pneumonia and NCD which were associated with rainfall (Egondi et al., 2012).

The main limitation of the above studies is that most of the analysis are based on the point estimates of sex, systematic literature review, qualitative or descriptive in nature, with very few individual or household controls. Furthermore, they mainly focus on mortalities in developed countries. Few empirical studies rigorously establish the effect of weather anomalies and decompose the total, direct and indirect effect of weather events through potential pathways, in addition to establishing the extent to which weather variables and health care factors contribute to the total observed health gap. The only study that examines the gender differentiated effect of weather extremes on health, and conducts a decomposition analysis is Zarulli et al. (2018). However, the decomposition of inequalities in life expectancy was to assess the contribution of age to the total gap in life expectancy and no other factors. Furthermore, the study does not establish the indirect effect.

The second strand of literature attempts to decompose the gender health gap in order to explain the source of the observed health different among men and women. Most of these studies focus on the contributions of sexual and health behaviours (Schünemann et al., 2017; Sia et al., 2014; Zhang et al., 2015) , awareness (Sia et al., 2014), age and mortality cause-specifics (Chisumpa & Odimegwu, 2018), and other socio-demographic, economic and geographical characters (Gächter et al., 2010; Murendo & Murenje, 2018) to the total health gap. There is no study that sought to find out how much of the was explained by differential exposures of weather anomalies.

Based on the highlighted limitations, the current study fills this gap by combining the two highlighted strands of literature and assesses the effect of weather anomalies at both intensive and extensive margins of illness among men and women, establishes the indirect effect of weather events through water scarcity pathways and further determines how much of the gender health gap is explained by weather factors, while accounting for health seeking behaviours and other individual specific factors. To our knowledge, this is among the first studies to examine jointly the effects of weather and health care variables on health, as well as decompose the total effect of weather events into direct and indirect effect as well as determine the contribution of different factors to the total health gap among women and women at both margins of illness.

**Theoretical framework**

This study relies upon previous related literature in identifying and modelling gender related factors that influence men and women health status or mortalities. From an economic perspective, Schünemann et al. (2017) indicates that there are limited theories to guide the discussions on gender health gap, because of over-emphasis on the Grossman (1972) health capital model in the previous decades. This study adopts a framework developed by Leung et al. (2004) that explicitly addressed gender related issues by analysing and explaining health gap between men and women during the economic development process. The structure adopted by Leung et al. (2004) is partly an extension of Galor and Weil (1993) model which employed a neoclassical growth theory taking into consideration gender differentials in endowments. Leung et al. (2004) and Galor & Weil (1993) considered an economy having two types of people, men and women who live up to three periods in their lifetime before dying. Whereby in old age and childhood, men and women are the same because they cannot work. However, men and women are different in adulthood because they make decisions, work during this period, are endowed with different labour inputs and earn different wages rates (Galor & Weil, 1993). Some of the income earned during the working period is used on health improvement. Therefore, the basic health production and mortality function of men and women during the working period as specified by Leung et al. (2004) is as follows;

$$H_{t,g} = A_g\,(t)\big(M_{t,g}\big)\,\big(Z_{t,g}\big) + \bar{H}\,, \quad g = male\ \ or\ female \tag{3.1}$$

Where $H_{t,g}$ is the health stock amount at the end of the working age, which is the summation of acquired health stock and the initial heath endowment ($\bar{H}$ ) during the working age period. A vector for health production technology is $A_g\,(t)$ while health investment goods and time are denoted by $M_{t,g}$ and $Z_{t,g}$ respectively. These two investments are responsible for production of new health stock that differs by gender (g). Given that health is also socially produced and Leung et al. (2004) did not model marriage market, our study also benefits from Felder (2006) who studied gender longevity gap among single men and women, and married couples, and Schünemann et al. (2017) who analysed preferences for health behaviours among the different gender groups.

Most importantly, we incorporate environmental or ecological factors to this framework because, health outcomes cannot be explained solely by individual characteristics, and some factors of health do not operate at an individual level (Diez-Roux, 1998) . From the modern theories of disease causation, most of the diseases are multicausal produced through interactions of different health factors and extends across levels, thus physical environment is acknowledged as one of the main risk factors (causes) of diseases (Diez-Roux, 1998; Gächter et al., 2010; Krieger, 2001; Najman, 1980). Climate variability is one of the environmental factors that we add to the framework since weather events and climate change affects health of people as well as their way of life (Commission on Social Determinants of Health, 2008). Joint inclusion of group level and individual level variables that shape disease and health are advocated for so as to complete understanding given that the group variables may limit choices made by individuals, affect the working conditions or affect individual health directly (Diez-Roux, 1998; Gächter et al., 2010).

**Conceptual framework**

Figure 3.1 presents the conceptual framework for this study based on gender differentiated health outcomes. Our study builds on the framework provided by World Health Organization (2014) on the interactions between climate and health, with a gendered perspective. Therefore, we highlight and study both the direct and indirect linkages between exposure to meteorological conditions and health outcomes.

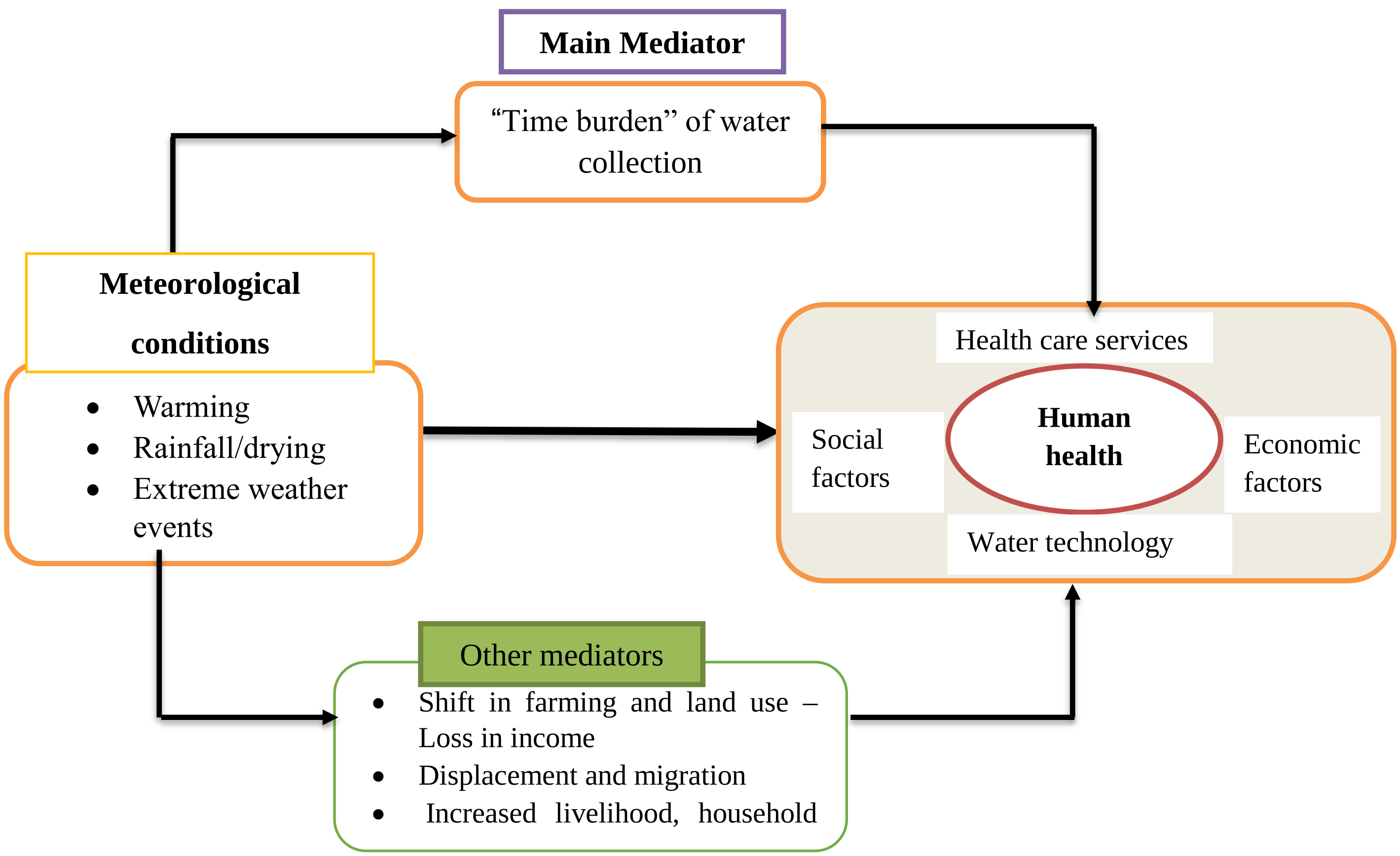


**Figure 3.1**: Relationship between climate or weather events and health, gender perspective

Furthermore, we acknowledge the interactions of different pathways with other non-climatic factors that are major determinants of health The direct effect of climate on health mainly occur through hazards such as droughts, floods, heatwaves and storms which lead to injuries and mortalities (Few et al., 2004; Smith et al., 2014; World Health Organization, 2014). Additionally, some of infectious diseases outbreaks, resulting from precipitation extremes are classified under the direct pathway (Few et al., 2004; World Health Organization, 2014), even though they occur post-onset period. The vulnerability to the abovementioned direct health effects differs by sex and is influenced by social-economic factors.

Indirectly, climate affects health through multiple mechanisms. In general, meteorological changes and extreme weather may affect the key determinants of human health which include water, food security, clean air, disease vectors and shelter (Sorensen et al., 2018; World Health Organization, 2014), thus exacerbating already existing diseases. For instance, rising temperatures may increase malaria transmission and pregnancy-induced hypertension whereas low temperature and increased precipitation may lead to pre-eclampsia in women (World Health Organization, 2014). Climate events may also affect distribution of pathogens responsible for foodborne diseases (Lake & Barker, 2018). Demand for water to meet household needs increases during drought, yet less quantities of water are available during dry periods (World Health Organization, 2014).

From a gender perspective, it's important to highlight that women and men have differing needs of water and nutrition in specific periods of their life. For instance, women have distinct nutritional and water demands during reproductive periods, especially during menstruation, pregnancy, child birth and lactation period: therefore, they are at more risk of suffering from health outcomes sensitive to climate such as anaemia, malnutrition, micro and macronutrient deficiencies as compared to men (Sorensen et al., 2018; World Health Organization, 2014). On the other hand, men have high nutritional requirement, especially energy and are more likely to suffer from severe famine (Neumayer & Plümper, 2007). Concerning gender roles, women especially in SSA are responsible for water provision (Graham et al., 2016; Sorensen et al., 2018; World Health Organization, 2014) storage and distribution for the family, and suffer more during periods of water scarcity caused by droughts, shifting rainfall pattern and high temperatures (Sorensen et al., 2018; World Health Organization, 2014). Other domestic and agricultural tasks are performed by women who spent more of their time around house and in the farm, increasing their exposure to mosquito breeding sites (Sorensen et al., 2018).

In this study, we focus on establishing the indirect effect occurring through the water access pathways. Specifically, time spent in water collection activities, because quantity per capita of water is reduced when individuals take longer time to walk to a water source, and this may adverse effect on human health (World Health Organization, 2014). Furthermore, women may be exposed to contaminated water sources due to weather events. Other mediators such as shift in farming and land use, displacement and migration and other burdens associated with increased livelihood, household and caring activities are presented in the framework because they have adverse effects on health (World Health Organization, 2014), especially in developing countries. However, they are out of scope of this study because of data limitations.

The different health outcomes associated with lack of access to sufficient and safe drinking water include illness, injuries and mortalities. Water related diseases increase during periods of droughts and floods (Prüss-Üstün et al., 2008) and water washed diseases resulting from poor hygiene practices are common when there is water scarcity. Taken together, climate events are likely to increase the disease burden attributed to WASH (Prüss-Üstün et al., 2008; World Health Organization, 2014). Some of the diseases related to WASH conditions fall into broader categories of faecal-oral transmission (water-borne or watershed diseases) which include; the diarrhoeas category that consist of severe diseases such as cholera, typhoid and dysenteries among others (Few et al., 2004; Prüss-Üstün et al., 2008). Other categories include water-washed diseases related to eye and skin infections, water-based diseases penetrating through the skin or ingested through contaminated water, soil-transmitted helminths, water-related insect vectors that bite near water or breed in water (Few et al., 2004).

Other negative health impacts resulting from spending more time collecting water and carrying heavy water containers over a long distance from water sources have also been documented. Water transport requires physical effort (Asaba et al., 2013; Geere et al., 2010; Heise et al., 2019), therefore women use a substantial amount of their daily energy intake of about 30% is spent by women fetching water (Sorensen et al., 2018; World Health Organization, 2014), especially during dry seasons, and when water is transported by head loading or hand lifting (Asaba et al., 2013). Long journeys with heavy pots of water may lead to spinal pain, back pain, head pain and neck pain (Geere et al., 2010), and potential cumulative damages to muscles (World Health Organization, 2014) and joints, early arthritis and related disabilities due to pressure exerted on the skeletal system (Graham et al., 2016). Furthermore, water transport may lead to exhaustion (World Health Organization, 2014), fatigue related injuries (Geere et al., 2010) and soft tissue damage (Graham et al., 2016).

Long distances to water source expose women to heat (Sorensen et al., 2018) and the risk of violence (Graham et al., 2016; Sommer et al., 2015; World Health Organization, 2014). Sexual violence and rape may occur along the way when women travel to fetch water, especially when water collection is carried out in the early mornings or late evenings while domestic violence may occur at home because of less water collected for household use, and more time spent collecting water, compromising other duties (Sommer et al., 2015). Furthermore, assaults, physical fights and verbal abuse among women over competition for the scarce water resource may occur at water collection points (Sommer et al., 2015). All these forms of violence may create anxiety, stress and fear that can consequently lead to mental stress. Injuries, sexual health problems and other negative health impacts may also be experienced as a result of violence (Sommer et al., 2015).

More time spent collecting water results into other economic costs that affect health. For instance, reduced schooling time for girls, less opportunities in the labour market for women (Sorensen et al., 2018; Sorenson et al., 2011), which makes them unable to access adequate health education or services.

Given the documented evidence of the linkages between water scarcity and health outcomes, households in poor rural settings adopt different technologies to enhance water supply and reduce the disease burden attributable to WASH (Cowden et al., 2008; Fry et al., 2010). One of the technologies used by most rural households is domestic rain water harvesting. Rain water harvesting increases water quantities for the household, thus enabling better sanitation and hygiene practices, and further improvement in health outcomes, especially for waterborne and water washed diseases (Fry et al., 2010).

## 3.3 Methodology

### 3.3.1 Data Sources

**LSMS –ISA data**

The study uses individual level and household level data from the four waves (2009-2014) of the LSMS-ISA surveys. Sampling was done at household level through the two-stage stratified cluster sampling, and the survey design in the different waves was maintained as the same (Uganda Bureau of Statistics, 2013). The total cumulative sample of rural individuals interviewed in the four waves was approximately 49,644 with 22,469 individuals in the working age category (aged between 15-64 years). This study focuses on this sub-sample only and not the other age-groups, given that most of the variables to be controlled for in the empirical analysis were collected for this group. Furthermore, this is the age-group that is economically active and where gender aspects are dominant. For instance, Heise et al. (2019) indicates that by age 10 most children have learnt restrictive norms, codes of conduct, and roles which are further monitored by parents and other community members.

This study uses the household questionnaire and data from the following sections; household roster, general information on household members, education, health and labour force status capturing individual specific information (Uganda Bureau of Statistics, 2011, 2013). Housing conditions, water and sanitation, household assets, dependency ratio and household food consumption sections were used even though the data was captured at household level.

**Weather data**

The georeferenced data in the UNPS enables us to match each household with temperature and rainfall data within a given enumeration area. Monthly rainfall data are extracted from the CHIRPS data version 2, (Funk et al., 2015) while the temperature data are from MODIS (Hooker et al., 2018; Wan et al. 2015).

### 3.3.2 Study variables

Given that health is an individual specific occurrence that accumulates in the household and influenced by environmental factors, individual specific variables as well as household level variables are considered in the empirical analysis.

The main outcome variables are self-reported individual measures of health status, in terms of self-reported morbidity, counts of sick days and work day lost (days of restricted activities) due to illnesses or injuries in 30 days prior to the interview. These variables were captured in the health section where all regular and usual household members were asked information on their health conditions. Information on number of sick days and work days lost were however collected for household members whose response was "YES" to the following question; "*During the past 30 days, did [name] suffer from any illness or injury?*". We also treat the morbidity dummy variable (YES/NO) as an outcome variable in the decomposition analysis detailing the contribution of weather effects in explaining the gender gap observed in terms of the illness occurrence.

There is no consensus on one measure of individual health (Schultz, 2010). Self-reported measures in terms of self-assessments and self-reported illness over a reference period are common measures of health. Some of the studies that have used self-reported health measures in terms of sick days, work days lost, a binary or categorical variable (including ranks) of self-reported health on general health or specific symptoms include (Giang & Allebeck, 2003; Harnois & Bastos, 2018; Lohmann & Lechtenfeld, 2015; Zhang et al., 2015). Even though measures such as functional limitations (Schultz, 2005) or clinical measures are preferred as true measures of individual health (Schultz, 2005) , the survey did not collect this information. However, days of work lost due to illness (a proxy of functional limitation and productivity losses) is included in our analysis as an alternative measure of health.

The mediator variable is time spent on water collection activities in hours, over the last seven days prior to the interview. This variable was captured in the labour force module (non-market labour activities) where all individuals over five years or respondents were asked this question "*In the last 7 days, how much time in hours did [Name] spend fetching water for the household, including travel time*?" The main explanatory variables are the respective weather variables and the health care variables. Weather variables comprise of both long-term and short-term measures of temperature and rainfall. Long-term measures are negative rainfall deviation – a dummy variable of (1= yes) if the annual rainfall deviation from the long-term annual mean was less than 0mm, and 0 dummy if otherwise. For temperature, positive temperature deviation is constructed with (1=yes) denoting annual average temperature deviation of greater than 0 from the long-term temperature. Furthermore, following Agamile and Lawson (2021) approach, we created additional weather variables for extreme negative rain deviation ( a dummy variable of 1 if the negative rainfall deviation values of annual rainfall from the long-term mean annual rainfall fell within the lower range (the 50th percentile and below) while extreme positive temperature deviation was 1 if positive temperature deviation fell within the upper range ( 50th -100th percentile). Rainfall deviation data was categorized into deciles only for individuals with negative rainfall deviation values while temperature for individuals with positive temperature deviation values. Figure 3.2 shows the distribution of rainfall and temperature deviation.

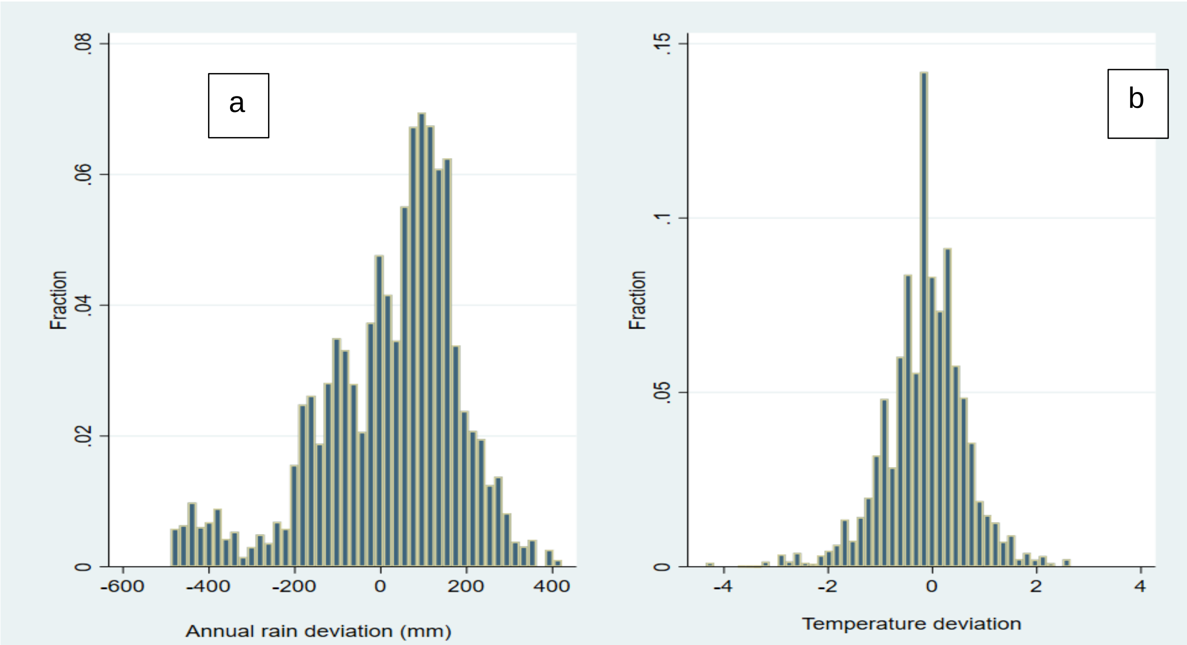


**Figure 3.2:** Distribution of annual rainfall deviation from mean -1981 to survey years (a) and temperature deviations from the mean – 2000 to survey years (b)

Source: Author elaborations from CHIRPS and MODIS data

The short-term measures are temperature and rainfall in the month prior to the interviews, including their quadratic terms, with the later variable (rainfall) transformed into logarithm values. Short-term variables are included in respective regressions because the outcome variables are based on a 30-day recall period. Each individual is matched with weather information in the respective enumeration areas.

The health care variables were collected at individual level given that the level of health consciousness varies among individuals. The specific health care variables used include; places where individuals consulted first (dummy variables for pharmacy, private hospital or doctor, government hospital or centre, distance to the health care centre in kilometres, and usage of treated mosquito nets). These health care variables were only collected for individuals who reported illness except, usage of mosquito nets. While the latter is preventive, the former variables are curative health care services. We consider the above health care services because, health care and other health behaviours have a direct effect on health outcomes, and play key roles in improving and explaining disparities in health status among individuals. For instance, Manandhar et al. (2018) argue that women access to health care services might be limited because of low education, income and lack of women autonomy on out of pocket payments, while masculinity and risk-taking behaviours of male may inhibit male from seeking health care).

Other independent variables included in the analysis such as age, marital status, occupation, education, wealth index and individual income are guided by literature focusing on the main determinants of health) (Felder, 2006; Giang & Allebeck, 2003; Grossman, 1972; Sia et al., 2014). For instance, education is known as an important determinant of health status since well-educated people are efficient producers of health, are more knowledgeable on health behaviours and preventive services hence use time more efficiently to produce health (Feinstein et al., 2006; Hemsley & Hollanda, 2020). In our study education is considered as a continuous variable of years of schooling.

Higher incomes also enable purchase of medical services and other health related inputs for health production thus improved health outcomes (Grossman, 1972; Hemsley & Hollanda, 2020). Two measures of income at individual and household level are considered in our study. Individual income variable (a categorical variable) is created from the labour force module where questions on labour were asked for all household members aged 5 years and above. Monthly income is first established from total cash and in-kind payments for main jobs and secondary jobs of the individuals involved in various occupation in the previous week before the interview. Other than using the continuous income variable, we create a categorical variable with four categories (0 for no income, 1 for income greater than 0 and less than or equal to 250, 000[14] Ugandan shillings, 2 for income greater than 250, 000 and less than or equal to 750,000 and 3 for income greater than 750,000[15]. Each individual is also linked up with household asset index constructed from PCA, as a measure of household wealth.

Occupation variables (dichotomous) for any paid work (salary or wage), business and farming are also derived from the labour-force section. Occupations under 'other category' treated as the base category included apprenticeship and voluntary work. We consider responses on questions seeking participation of individuals in the past 12 months before the interview rather than 7 days. Marital status was measured as categorical variable. However, dummy variables on whether an individual was married monogamously (base category), polygamously, divorced or separated, widow/ widower and never married are created and used in the analysis. Marital status is classified as a social determinant of health considering that it can enhance as well as be detrimental to health. There is extensive literature on marriage and longevity, especially in the developed countries (Gellatly & Störmer, 2017). Some of the benefits of marriage include low stress levels, division of labour, support among the couples, networks and more material resources (Ballantyne, 1999). However, the costs and benefits of marriage are different among men and women with women bearing most of the costs associated with multiple roles, stress and poor health (Ballantyne, 1999; Gächter et al., 2010). Child marriage in particular is a threat to both physical and psychological health of the female involved (World Health Organization, 2012). Furthermore, the quality of marriage matters on health (Lawrence et al., 2019). Given a range of covariates to be included in the models, we test for multicollinearity using the variance of inflation factor (VIF) where values of covariates without quadratic terms are less than 5.

### 3.3.3 Empirical strategy

**Two-part and hurdle count models**

The primary outcome of this study is individual health status measured in terms of illness, that is, the number of days an individual was sick, and the number of work days lost due to the illness. These two outcome variables were only reported by a subsample of individuals (approximately a third of the total sample) who were sick in the 30 days prior to the interview. For the rest of the sampled individuals, a positive random variable was not observed given that there was no occurrence of illness, hence the outcome value was assumed to be zero, occurring in a substantial number of observations as shown in the left panel of Figure 3.3**.** Therefore, this warrants estimation strategies designed to address and deal

[14] The average exchange rate of 1 USD was 1707 UGX in 2010, 2412 in 2011 and 2584 in 2013 (https://www.exchangerates.org.uk/USD-UGX-spot-exchange-rates-history)

[15] These were treated as dummy variables in the subsequent regressions.

with the problem of limited dependent variables, in order to account for the excess number of zeros (Belotti et al., 2015).

In this study, we specifically utilize the two-parts model (TPM) of Belotti et al. (2015) because of the nature and distribution of our outcome variables (large number of zeros, skewness and counts). Conceptually, TPM is richer than a one-part model given that it allows decomposition of one random variable into two distinct observed random variables Y>0 and Y|Y>0, having different densities (Duan et al., 1984). Furthermore, our main goal is to investigate and distinguish the covariates that affect the propensity of being sick or stop working, from those factors affecting the number of days an individual was sick, and the number of work days lost, once the illness occurs. We rely on the assumption that there is no correlation of the error terms between the continuous and the binary equations (Belotti et al., 2015). Additionally, we assume that the zeros in the outcome variable are true zeros and not missing values as it is in Heckman and Tobit cases (Belotti et al., 2015; Duan et al., 1984).

TPM model that enables separate estimations of covariates effects on the outcome variable at both the extensive and intensive margins, and further establish the overall effect is ideal for our study (Belotti et al., 2015; Colchero et al., 2017; Deb & Norton, 2018). In the first part of TPM, the outcome is binary in nature, that is whether an individual suffered or recorded any day of illness /day of work lost in the month prior to the interview or not. Thus, a binary choice model, either logit or probit is used in predicting the probability that an individual has any illness or lost any work day due to illness, and in estimation of the factors that determine the probability of being ill, on the full sample. The general specification predicting the likelihood of a positive outcome in the first part is specified as follows;

$$\Pr(Y_{it} > 0) = \gamma_0 + \gamma_1 X_{1i} + \gamma_2 X_{2it} + \mu_i \qquad (3.2)$$

where $Y_{it}$ is the number of sick days or days of work lost due to illness for individual $i$ in year t, $x_{1it}$ is a vector of individual or household variables that are determinants of illness such as; age, income, marital status and education. $x_{2it}$ is a vector of variables that represent the different weather variables such as, temperature and rainfall, assumed to be exogeneous and random. Our coefficient of interest is $\gamma_2$ which measures the total effect of specific weather events on probability of illness

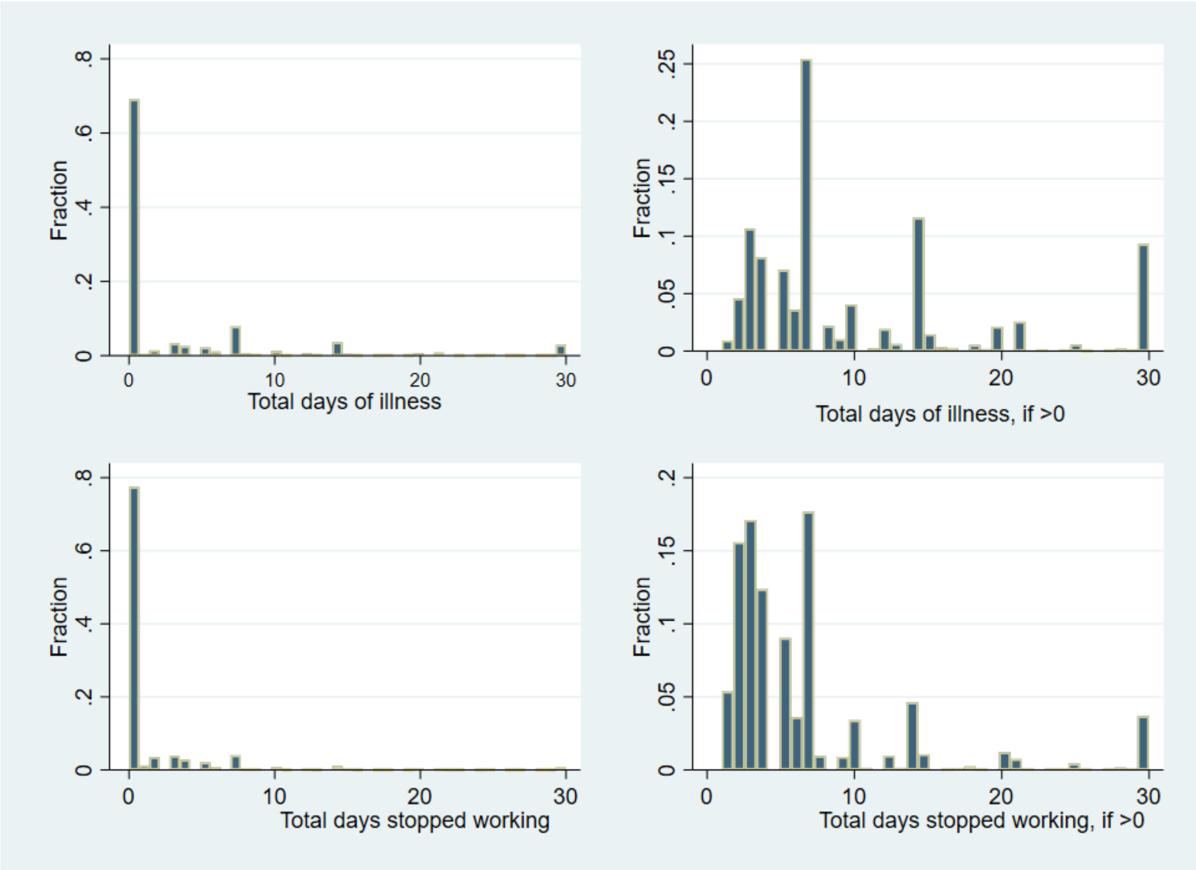

**Figure 3.3**: Proportion of individuals with different days of illness and lost work days.

Separate regressions models are estimated for men and women subsamples, however in the total sample estimation, a sex covariate is also added. We add subscript $t$ on each covariate since we also control for year dummies of the different survey years. We specifically fit the above estimation using a logit model with a logistic distribution.

In the second part, a conditional equation is used to model the outcome variable on a subsample of individuals with positive outcomes (who suffered illness or had at least one day of illness or lost at least one work day). Maintaining the same independent variables used in the first part estimation, the general estimation of the second part is specified as;

$$E(Y_{it}|Y_{it} > 0) = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \varepsilon_{1t} \tag{3.3}$$

Our main coefficient of interest is still ($\beta_2$) on the weather variables ( $X_{2i}$) which measures total effect of specific weather variables on days of illness, conditional on being sick and $\varepsilon_{it}$ is the error term. The choice of the model in the second stage is critical since this has implications on the estimated results (Deb & Norton, 2018). Assuming our outcome variable is a continuous variable, the generalized linear model (GLM) that can naturally accommodate skewness and is flexible in providing several functional forms and mixed distributions was used as opposed to the OLS (Blough et al., 1999; Deb & Norton, 2018). We fit the GLM model in the second stage using the log link function and gamma as the distribution family, using robust standard errors for statistical corrections, in case of any consistencies arising from the choice of family and link. Given that the same set of covariates were used in both parts of the model, expected total days of illness for individual $i$ is therefore equal to individual probability of having days of illness multiplied by the conditional number of days of illness. The general specification that applies also to expected total days of stopped working is specified as follows;

$$\begin{aligned} E\ (Y_{it}) &= \Pr(Y_{it} > 0) * E(\ Y_{it}|Y_{it} > 0) \\ &= (\gamma_0 + \gamma_1 X_{1it} + \gamma_2 X_{2it} + \ \mu_{it}) * (\ \beta_0\ + \beta_1 X_{1it} + \beta_2 X_{2it} + \varepsilon_{1t}) \end{aligned} \tag{3.4}$$

Equation 3.4 above enables us to establish the total effect of weather variables on number of days of illness for the overall total sample and overall sample of men and women regardless whether they were sick or not. In estimating equation 3.3 and 3.4 above, we assumed continuous outcome variable and used GLM in the second stage. However, our main dependent variables are nonnegative counts (number of days). Therefore, we repeat these estimations using the two-part model for count data for robustness checks. (Deb & Norton, 2018) indicate that there are significant losses in statistical power in models that ignore the discrete nature of the data, and this can further result into inconsistent estimates of the parameters (Vistnes, 1997).

In particular, we adopt the hurdle negative binomial model (HNBM), with logit in the first part to model the participation decision, and truncated negative binomial (TNB) in the second part in estimating the participation extent to the individuals that cross the hurdle. We choose HNBM because this combination has been recommended and used in many health applications previously (Deb & Norton, 2018; Pohlmeier & Ulrich, 1995; Vistnes, 1997). For overall effect, we use negative binomial method separately on the total samples. Generally, the negative binomial (NBM) results into more efficient and unbiased estimates in presence of high number of zeros and skewed data as opposed to Poisson (Cameron & Trivedi, 1986; Greene, 2008; Ver Hoef & Boveng, 2007). The specification for the first and second part of the HNBM uses the same covariates as earlier explained, as well as for overall effect. The only difference is that the outcome variable is treated as discrete as opposed to continuous. The second part of the hurdle (TNB), using exponential conditional mean is specified as follows;

$$E(Y_{it}|Y_{it} > 0) = \exp(\alpha + x_{it}\beta + \varepsilon_{2it}) \tag{3.5}$$

One of the main determinants of individual health status is the use of health care services, which was collected only on the sub-sample of individuals who reported illness and consulted different health providers. These health care variables were not included in the previous estimation because they were irrelevant for individuals whose outcome variable was zero, and those with positive values but did not consult or seek any medication. In order to assess, the effect of the health-seeking behaviours on the number of sick days or unproductive work days, we estimate the second part of the model separately, using a single index model controlling for health care variables, in addition to the earlier socio-economic as well as weather controls. The general specification of the model is as follows

$$E(Y_{it}|Y_{it} > 0) = \ \beta_0\ + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon_{3it} \tag{3.6}$$

Where $X_{3it}$ is a vector denoting health care variable, including distance to the health facilities. $X_{1it}$ and $X_{2it}$ remains as earlier defined. Since the coefficients of the probit, GLM and NBM are not interpretable, the average marginal effects that estimates the predicated probabilities are reported for all our estimations.

**Direct and Indirect effect analysis.**

This study hypothesizes that the total effect of climate or weather events on health operates both directly, and indirectly by influencing the time spent in water collection by individuals (*see the conceptual framework for the hypothesized relationship*). Therefore, establishing the total effects, and the magnitude of direct and indirect effects relative to the total effect is crucial (Breen et al., 2013; Kohler et al., 2011). We adopt principles of path analysis (Breen et al., 2013) where effect of weather events ($X_{2it}$) on health outcomes ($Y_{it}$) is decomposed into two parts, with and without mediator variables – water collection time ($Z_{it}$). In (equation 1), the mediator variable was omitted in the respective regressions, enabling estimation of the total effects (sum of direct and indirect effect). Therefore, we present analysis that enables us to quantify direct effect, and the degree to which water collection time mediates the relationship between weather events and health outcomes (indirect effect), using "difference in coefficients methods" while holding other factors constant. Breen et al. (2013) estimations shows that "difference in coefficients methods" is similar to "product of coefficients methods" extensively used in linear models.

Our key variables are weather events with statistically significant coefficients in (equation 3.2), because they provide evidence for existence of the hypothesized relationship. To measure this mediation, we adopt KHB method proposed by Karlson, Holm and Breen that enables cross-model coefficients comparisons of two nested non-linear models, and also enables average partial effects estimations (Kohler et al., 2011). We only conduct the decomposition analysis at the extensive margin, on the binary response model. For clarity purposes we present the reduced model in the previous sub-section (equation 3.7, similar to equation 3.2), using the same set of covariates and include the mediator variable ($Z_{it}$) in the full model (equation 3.8) as shown below;

$$\Pr(Y_{it} > 0) = \gamma_0 + \gamma_1 X_{1i} + \gamma_2 X_{2it} + \mu_i \tag{3.7}$$

$$\Pr(Y_{it} > 0) = \alpha_0 + \alpha_1 X_{1i} + \alpha_2 X_{2it} + \alpha_3 Z_{it} + \mu_i \tag{3.8}$$

The two equations are the same, with the exception of the mediator variable in equation 3.8. Weather variables denoted by $X_{2it}$ are our key variables in both the reduced model and full model, and the coefficients $\gamma_2$ and $\alpha_2$ represent the total effect and direct effect of specific weather variable respectively. The difference between coefficients of same weather variable ($\gamma_2$- $\alpha_2$) in the two regression equations is the indirect effect. It represents the magnitude to which weather and health relationship is mediated or explained by water collection time, holding another factors constant ($X_{1i}$). Same covariates that are common determinants of $X_{2it}$, $Z_{it}$ and $Y_{it}$ are used as recommended (Breen et al., 2013; Kohler et al., 2011). For interpretation of coefficients on a probability scale, we estimate the average partial effects (ape) using KHB command in STATA (Kohler et al., 2011) . However, we rely on the logit coefficients for significance test for the effect differences (Kohler et al., 2011), since ape option does not provide this statistic. Other statistics of importance include the percentage reduction and confounding ratio which measures the percentage change in each key variable coefficient due to confounding, and impact of confounding net of rescaling respectively (Kohler et al., 2011). KHB method also enables estimation of more than one key variable in the same command and further disentangles contribution of several mediators (Kohler et al., 2011).

Other tests required to establish if $Z_{it}$ confounds $X_{it}$ are as follows. Significant correlation between weather events ($X_{2it}$) and pathway variable $Z_{it}$ – water collection time (*path a*), and a direct and significant effect of the pathway variable ($Z_{it}$) on probability of illness ($Y_{it}$) (*path b*), Therefore, we use a two-step procedure to estimate separate regressions using the same covariates on the respective regressions. To fully support the existence of the outlined mediated relationships, all paths (a and b) should be statistically significant, in addition to path c's, with (c') and without mediators (c), as well as their differences (c- c'). Partial mediation process is when any of the paths is insignificant while the others are significant (Calic & Mosakowski, 2016).

**Identification assumptions**

The identification conditions for mediation analysis to have a causal interpretation both in observational studies and randomized experiments requires satisfaction of two sequential ignorability assumptions (SIA). According to (Breen et al., 2013; Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010) the key assumptions are as follows, 1) The predictor variables (weather variability variables in our case) are conditionally independent of unobserved characteristics, given observed covariates and 2) the mediator variable (water collection time) is also conditionally independent of unobserved characteristics, given other background covariates and predictor variables. However, the second assumption is too strong in many applied settings and not easily testable even in randomized experiments (Breen et al., 2013; Imai, Keele, & Tingley, 2010) because as much as the treatment variable is randomized, the mediator variable is not, thus creating a self-selection bias.

For the first assumption, even though we do not use experimental data, we argue that this assumption is partly satisfied given that the predictor variables were exogeneous constructed from remotely sensed data sources as opposed to self-reported measures that are likely to be endogenous. We assume that weather variability is random and uncorrelated with unobserved factors since some of the weather variability measures were deviations from long-term mean. Previous studies that treated weather variability and events as exogeneous variables and potential instruments for causal inference in their studies include (Antonelli et al., 2020; Asfaw et al., 2016; Omiat & Shively, 2020). Furthermore, we add as many covariates in our model as possible in order to increase the ignorability of treatment assignment thus strengthening the validity of the outlined identifying assumptions for causal mediation analysis. However, we do not rule out the possibility of existence of unobserved confounders that may affect both the outcome and the mediator variable. Therefore, since we cannot test the second assumption on ignorability of the mediator and do not conduct sensitivity analysis on this non-testable assumption, we do not claim causal effects.

**Gender gap decomposition analysis**

After assessing the determinants of sick days and work days lost, we conduct a decomposition analysis in order to estimate the gender differences in the health status, and explain the source of these differences based on the gender-specific factors that contribute to the observed health inequalities. O'Donnell asserts that the next natural step after measuring health inequalities is seeking to explain them, and Blinder–Oaxaca decomposition analysis enables this (O'Donnell et al., 2010). However, given the non-linear nature of our outcome variables (binary and counts) , we adopt Powers et al. (2011) multivariate decomposition method for non-linear models, which is an extension of Blinder–Oaxaca. Unlike other non-linear decomposition that are limited in their decomposition, the multivariate decomposition provides estimates for both the overall decomposition and detailed decomposition, thus allowing assessment of each covariate contribution to the different components of the gap (Powers et al., 2011). Furthermore, the method addresses problems of path dependency and identification problem due to the reference categories chosen for the dummy predictor variables (Powers et al., 2011). Path dependency and identification problems are solved by use of weights and normalization of the dummy variables such that decomposition is invariant on how the variables are entering the decomposition and, on the reference category chosen (Powers et al., 2011).

Using women subsample as the comparison group and men as the reference category. The overall decomposition of the women-men aggregate gap in health outcome is specified as;

$$\bar{Y}_w - \bar{Y}_m = \left[F\left(\bar{X}_w\hat{\beta}_w\right) - \left(\bar{X}_m\hat{\beta}_w\right)\right] - \left[F\left(\bar{X}_m\hat{\beta}_w\right) - \left(\bar{X}_m\hat{\beta}_m\right)\right] \tag{3.9}$$

Where $\bar{Y}_w - \bar{Y}_m$ , is the mean differences in the health outcomes between women and men. The first part $\left[F\left(\bar{X}_w\hat{\beta}_w\right) - \left(\bar{X}_m\hat{\beta}_w\right)\right]$ is due to composition differential between men and women, also known as the explained component given that it is due to the differences in characteristics or endowments between the two groups (Jann, 2008; Powers et al., 2011). The explained component is the counterfactual comparison of health differences from the women perspective, interpreted as the difference expected in health outcomes if women are given men covariates. In our case such characteristics include; age, education, health seeking behaviours, marital status, as well as the weather variables. The second part $\left[F\left(\bar{X}_m\hat{\beta}_w\right) - \left(\bar{X}_m\hat{\beta}_m\right)\right]$ is known as the coefficient effect or unexplained component which is due to differences in coefficients, behavioral responses or returns. This part captures any possible effects of the characteristics and is also attributed to discrimination (Jann, 2008). The unexplained aggregate contribution is interpreted as the expected difference in health outcomes if men experienced women behavioral responses.

After assigning the weights, the final decomposition of the raw aggregate gap is expressed as a summation of the weighted total of each factor unique contribution as shown below;

$$\bar{Y}_w - \bar{Y}_m = E + C = \sum_{k=1}^{K} W_{\Delta X_k} E + \sum_{k=1}^{K} W_{\Delta X_k} C = \sum_{k=1}^{K} E_k + \sum_{k=1}^{K} C_k \tag{3.10}$$

Where $W_{\Delta X_k}$ is the decomposition weights, E and C are the explained and unexplained components respectively. Based on our outcome variables (binary and counts), we use logit (for the gap differences on the probability of illness) and negative binomial decomposition approaches (for the gap differences on sick and restricted days).

## 3.4 Results

### 3.4.1 Descriptive statistics

The socio-demographic, economic and weather characteristics of men and women in the working age group are presented in Table 3.1. On average, women constituted 51% of respondents, and were relatively older (32 years) than men, aged 31 years. The proportion of men and women in the different survey years was almost similar, with no significance differences. Educational attainment levels were significantly lower in women than men, with a difference of approximately 1.5 years. The small gap in education attainment reveal substantial progress made by women in catching up with male education levels in the recent years.

With regards to occupational inequalities[16], more women participated in unpaid agricultural activities (87%) in their respective household's farms, while men were more involved in paid work, either in agricultural or non-agricultural sectors (28%) during the 12 months prior to the interview. The proportion of men and women involved in business was almost the same, even though the mean difference was significant. Indeed, more women (89%) reported that they did not earn any personal income in the week prior to the survey compared to men, who dominated the upper income categories. Approximately 5% of men earned more than 250,000 UGX per month as compared to 1% of women, with the corresponding income. A female disadvantage of about 13 percentage points in total for paid work and business activities, and 11 percentage points in income despite a small difference in education attainment provides evidence for gender occupational sorting, partly shaped by the societies (Schieder & Gould, 2016), especially in developing countries.

[16] Possibility of being engaged in more than one occupation.

**Table 3.1**: Summary statistics of working age individuals

| Category | Variable | Total Sample) (N = 22,469) | Women (N= 11,568) | Men N= (10,901) | Difference |
|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 |
| Socio-economic Information | Age (years) | 31.382 | 31.971 | 30.757 | 1.214*** |
| | Education (years) | 5.785 | 5.059 | 6.555 | -1.495*** |
| | ***Occupation*** | | | | |
| | Salaried /wage (1 = yes) | 0.218 | 0.161 | 0.279 | -0.118*** |
| | Business (1 = yes) | 0.177 | 0.172 | 0.183 | -0.010** |
| | Farming (1 = yes) | 0.835 | 0.866 | 0.802 | 0.064*** |
| | **Income** | | | | |
| | No personal income (1 = yes) | 0.833 | 0.886 | 0.777 | 0.109*** |
| | Income (1-250000 UGX) | 0.134 | 0.100 | 0.171 | -0.070*** |
| | Income (250001-750000) | 0.027 | 0.012 | 0.043 | -0.032*** |
| | Income (>750000) | 0.005 | 0.002 | 0.009 | -0.007*** |
| | **Marital status** | | | | |
| | Married monogamous (1 = yes) | 0.402 | 0.411 | 0.392 | 0.018*** |
| | Married polygamous | 0.131 | 0.151 | 0.109 | 0.043*** |
| | Divorced / Separated | 0.057 | 0.079 | 0.034 | 0.045*** |
| | Widow/Widower | 0.039 | 0.070 | 0.006 | 0.065*** |
| | Never married | 0.371 | 0.289 | 0.459 | -0.170*** |
| | ***Other factors*** | | | | |
| | HH Asset Index | -0.472 | -0.483 | -0.460 | -0.024 |
| | Water harvesting | 0.014 | 0.014 | 0.014 | 0.000 |
| | Irrigation use | 0.017 | 0.017 | 0.018 | 0.001 |
| | Dependency ratio | 126.0 | 135.2 | 116.3 | 18.93*** |
| Intermediate variables | Water time | 3.174 | 4.386 | 1.887 | 2.499*** |
| | Water quantity | 64.326 | 63.784 | 64.902 | -1.119 |
| Other variables | Time firewood | 1.608 | 2.453 | 0.711 | 1.743*** |
| | Time agriculture | 8.984 | 9.623 | 8.306 | 1.317*** |
| | HDDS | 7.781 | 7.762 | 7.801 | -0.038 |
| Weather variables | Negative rain deviation (1=yes) | 0.382 | 0.378 | 0.385 | -0.007 |
| | Positive temperature deviation (1=Yes) | 0.412 | 0.411 | 0.414 | -0.003 |
| | Rainfall (month mm) | 107.6 | 106.9 | 108.3 | -1.309 |
| | Temperature (month mm) | 29.18 | 29.23 | 29.12 | 0.112** |
| Health seeking behaviours & variables | Mosquito net use (1=Yes) | 0.485 | 0.516 | 0.452 | 0.064*** |
| | Treated mosquito nets (1=Yes) | 0.396 | 0.423 | 0.367 | 0.056*** |
| | Illness consulted[17] (1=Yes) | 0.879 | 0.881 | 0.876 | 0.006 |
| | Distance to health facility[18] (Km) | 4.596 | 4.797 | 4.301 | 0.496** |
| | Government hospital (1=Yes) | 0.339 | 0.369 | 0.295 | 0.074*** |
| | Private hospital/doctor (1=Yes) | 0.355 | 0.341 | 0.375 | -0.035*** |
| | Pharmacy or shop (1=Yes) | 0.248 | 0.231 | 0.274 | -0.043*** |
| | Other healthcare[19] (1=Yes) | 0.050 | 0.052 | 0.047 | 0.006 |
| Year dummies | Year dummies (2009) 1=Yes | 0.251 | 0.251 | 0.252 | -0.002 |
| | Year dummies (2010) 1=Yes | 0.226 | 0.226 | 0.225 | 0.002 |

[17] The observations are only for those who incurred some illnesses and not the total sample (N= 6,965, women= 4,130, women = 2,835)

[18] The sample is only for those who incurred some illness and sought consultations (N= 6,127, women= 3,641, men= 2,486). The same applies healthcare usage.

[19] This includes traditional healer, friend and relative, religious institutions, NGO based community distributor, outreach, government community-based distributor,

| | | | | |
|---|---|---|---|---|
| Year dummies (2011) 1=Yes | 0.252 | 0.253 | 0.251 | 0.001 |
| Year dummies (2013) 1=Yes | 0.271 | 0.270 | 0.272 | -0.002 |

*** p<0.01, ** p<0.05, * p<0.1

Generally, a high proportion of men - approximately a half of men were never married, while only a third of the women were single. However, the proportion of women divorced, separated and widowed was significantly higher than that of men. Findings on divorce rate (6% for all individuals) is consistent with The Hague Institute for Innovation of Law (2020) who indicated that 7% of total adults in Uganda experience divorce or separation in the past four years and 4% based on their analysis. Furthermore, they noted that women are more likely face divorce or separation and they perceive it as a serious legal problem as compared to their counterparts. Similar trends are reported by Uganda Bureau of Statistics (2018) where among the divorced individuals, more females (68.2%) were divorced as compared to males. Given that rural, uneducated and poor women are more vulnerable and helpless when family is dissolved and might want to stay in abusive relationship because of financial limitations (The Hague Institute for Innovation of Law, 2020), divorce is more of a result an empowerment. It is noted that nowadays more women in Uganda are empowered and they initiate divorce in order to leave abusive or bad marriage (Karumuna, 2015). However, given that having children increases likelihood of divorce or separation (The Hague Institute for Innovation of Law, 2020), divorce could still be a sign of exclusion. Indeed, World Bank (2018) indicates that impact of divorce in Africa affects women more and they may be socially excluded and loose property and home when the marriage ends.

On health behaviours and health care use, more women used treated mosquito nets than men at 42% and 37% respectively with significant differences at 1% level. The proportion of women who suffered illnesses and sought consultations was similar to that of men with no significant imbalances between the two groups. Furthermore, both men and women who did not seek consultations gave similar reasons, that is, illness was mild, the available facilities were costly, the facilities were too far and in-availability of drugs[20]. On the other hand, gender differences in health care seeking behaviours were noted for the sub-sample of individuals who sought consultations. While more women (37%) reported to have visited the government hospital or health care centres for first consultations, a significant proportion of men visited private hospitals and doctors (38%), and pharmacy or drug shop (27%) than women at 34% and 23% respectively. Significant differences in distance to the health facilities were also reported, where the health facilities consulted by women were far away – a difference of 0.5 kms as compared to men health facilities.

The low economic status of women partly explains why more women sought treatment at the government hospitals, and travelled long distances to access health care. This is because of the affordability of health care in public health facilities given that user fees in Uganda were cancelled in 2001, with the aim of enhancing access by the poor (Burnham et al., 2004; Kwesiga et al., 2015; Ssewanyana et al., 2004). However, inefficiencies in the government hospitals, makes private health care centres and hospitals preferred choices by citizens (Burnham et al., 2004; Ssewanyana et al., 2004), though not affordable for the poor rural individuals. More so, rural women who have no income sources. Self-medication also

[20] These results are not reported in the table.

seemed to be a common practice given that 25% of the total individuals first consulted pharmacy, drug or general shops.

Household asset index, water quantity, sanitation and hygiene measures, and dependency ratio were not captured at individual level but rather at household level. In general, there was no significance differences between women and men in these measures, except for the dependency ratio which was high in women households. Likewise, there was no significance differences in the weather variables between men and women geographical areas, except temperature experienced in the month prior to the survey. Over a third of men and women experienced annual rainfall amount lower than the long-term mean, and annual mean temperature above the medium-term average.

Concerning the main intermediate variables, we present statistics on water source as well as sanitation and hygiene practices because time spent collecting water is dependent on the source of water, and lack of enough water compromises good hygiene practices. Women spent more time collecting water as compared to men, with significant differences. On average, women spent 4.4 hours collecting water in the last 7 days before the interview while men spent 2 hours as shown in Figure 3.4 (a). On a daily basis, this is about 40 mins of water collection. It's difficult to compare this statistic against the WHO and UNICEF JMP on water-sanitation time cut-off that defines the basic water access, since information on the number of trips was not provided.

Water collection time varied tremendously by region. Women in the northern region spent approximately 8 hours of water collection (more than twice the time spent by women in central and west), despite majority of households (80%) in the north accessing water from improved water sources as shown in Figure 3.4 (c &b). Domestic rain water harvesting for household use was high in central and western part of Uganda, and women in these regions spent less time in water collection activities. However, the proportion of households using unimproved water sources was high in those two regions. Participation of men in water collection activities was higher in the eastern region as compared to men in other regions, as shown in Figure 3.4(c). Additionally, men and women in central region spent almost the same number of hours in water collection activities. Overtime, there was an improvement in men's time allocation to water collection activities, and a reduction in time women spent on water collection as shown in Figure 3.4 (d), which partly signifies progress towards gender equality in division of household labour.

On sanitation facilities, at least 60% of the households used covered pit latrines, 80% had no handwashing facility at the toilet, while 20% of the households in north had no toilet facility and used bush as shown in Figure 7.2 of the appendix. The mean water usage by households was 64 litres[21] per day. Women also spent more time on agriculture (10 hours) and collecting firewood (2.5hours) as compared to men – 8 hours and 0.7 hours respectively as shown in Figure 3.4 (a). Agriculture and firewood are some of the activities that are affected by climate variability and climate change.

[21] This could be high because in 2013, they collected data on quantities of drinking water alone while in 2009-2011, data was collected on total quantity of water used by the household per day.

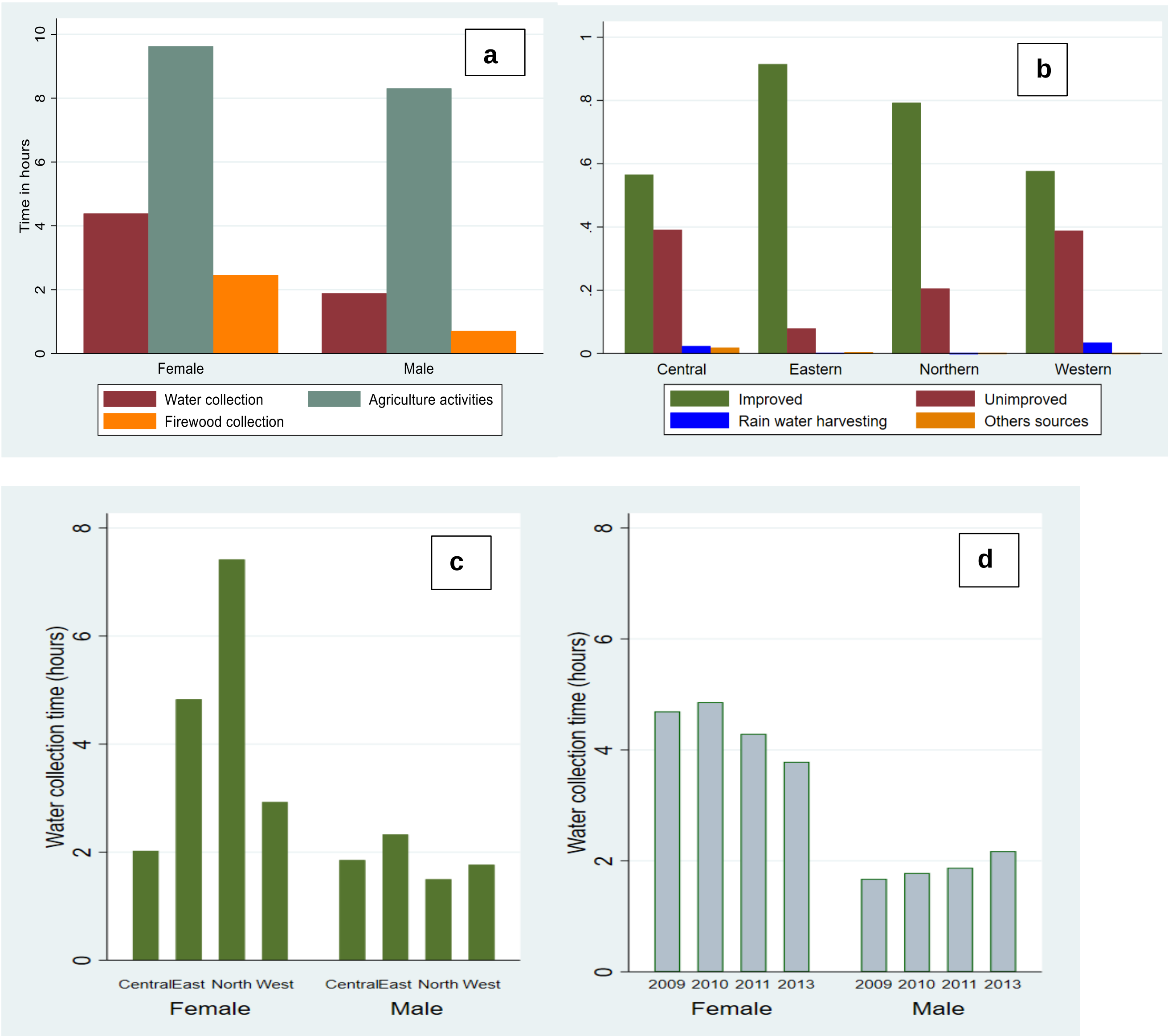


**Figure 3.4**: Time allocation to different activities among men and women (a), water sources[22] (b), and water collection time, among men and women by region (c) and survey year (d)

### Outcome variables

The descriptive statistics of outcome variables shown in Figure 3.5 (a) and Table 3.2 reveal women health disadvantage in general, as compared to the men, over the four survey periods. On average, the proportion of women reporting occurrence of illness was significantly higher than men at 36% and 26% respectively. Similarly, approximately a third of the women (26%) were unable to continue with their usual activities due to the illness, while only 19% of men reported inability to continue with their work activities. The symptoms of the major illness suffered by both men and women are shown in Figure 3.5 (b), where fever,

[22] Improved water sources include private connection to pipeline/piped water into dwelling, yard, public tap, borehole, protected well/spring, gravity flow scheme, vendor/tanker/truck, bottled water. Unimproved sources include, unprotected well or spring, river/stream/lake/pond,

headache, coughing, weakness, abdominal pains, chills, diarrhoea and wounds accounted for a substantial proportion of illness in both men and women.

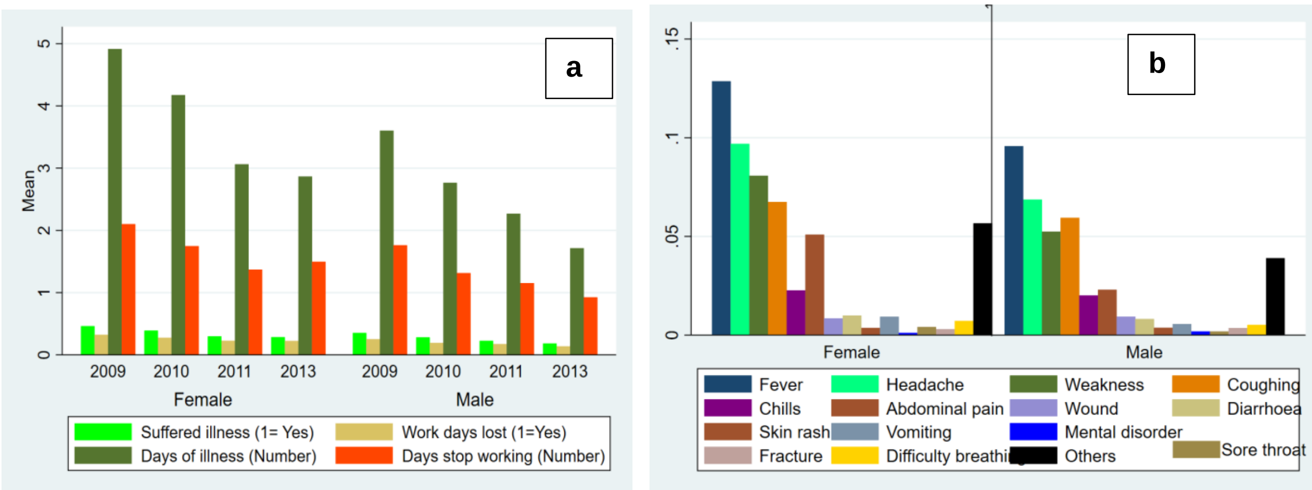


**Figure 3.5;** Health trends in men and women over the survey years (a), and symptoms (b)

Concerning the number of days of illness and working days lost due to the illness in the 30 days prior to the interview, women reported 3.7 and 1.7 days on average for the total sampled women, while, men reported 2.6 and 1.3 days respectively as shown in Table 3.2. More number of days were reported for the subsample of individuals who had experienced at least one illness, that is, 10.4 days of illness and 6.4 days of restricted work for women. The corresponding figures for men were 9.9 and 6.8 respectively. The differences in health outcomes between women and men were positive and statistically significant at 1% level, except for the work days lost where the difference was negative for the subsample and significant at 5% level. The pattern of health outcomes in women and men was consistent over the survey years – women reporting significantly poorer health on all health measures than men, even though poor health followed a declining trend for both groups over the four survey years as shown in Figure 3.5.

Our findings on health disparity among men and women in adulthood are consistent with other studies in social science research on illness and health as highlighted by Macintyre et al. (1996). It's often argued that there are gender differences in how symptoms are perceived, acted upon and evaluated. Women are widely assumed to be ready and more likely to report illness, and seek assistance as compared to men, thus high rates of morbidity in women, especially with regards to acute illness (Macintyre et al., 1996). In most societies, women are socialized to accept, admit that they are ill and can freely discuss their illness and seek help while men are self-reliant and stoic thus can tolerate pain without complaining, discussing it with their peers or seeking help from health professionals. In fact, reluctance to consult the doctor is one of the major obstacles of improving men's health (Banks, 2001). Men often seek help late when the disease advanced and serious and this late diagnosis could explain why men have high mortality rates than women (Banks, 2001). Masculinity behaviour in men is responsible for men's reluctance to seek medical attention and poor health outcomes, since illness is associated with weakness, vulnerability and dependence (Evans et al., 2011).

**Table 3.2**: Main outcome variable statistics, over the survey years

| | N | Variable | All individuals | | Women | | Men | | Difference |
|---|---|---|---|---|---|---|---|---|---|
| | | | Mean | SD | Mean | SD | Mean | SD | |
| **Panel A** | 22,469 | Suffered illness (1=Yes) | 0.310 | (0.462) | 0.357 | (0.479) | 0.260 | (0.439) | 0.097*** |
| All years | 22,469 | Days illness | 3.173 | (6.522) | 3.734 | (6.925) | 2.578 | (6.008) | 1.156*** |
| | 6,971 | Days of illness if >0 | 10.227 | (8.060) | 10.446 | (8.003) | 9.908 | (8.133) | 0.538*** |
| | 22,469 | Stopped working (1=Yes) | 0.226 | (0.418) | 0.262 | (0.440) | 0.189 | (0.391) | 0.073*** |
| | 22,469 | Days stopped working | 1.484 | (4.084) | 1.674 | (4.148) | 1.283 | (4.006) | 0.390*** |
| | 5,084 | Days stopped working if >0 | 6.560 | (6.359) | 6.394 | (5.962) | 6.804 | (6.896) | -0.410** |
| **Panel B** | 5,648 | Suffered illness | 0.411 | (0.492) | 0.463 | (0.499) | 0.356 | (0.479) | 0.107*** |
| | 5,648 | Days illness | 4.301 | (7.414) | 4.931 | (7.727) | 3.638 | (7.009) | 1.292*** |
| 2009 | 2,322 | Days of illness if >0 | 10.463 | (8.322) | 10.643 | (8.252) | 10.215 | (8.414) | 0.429 |
| | 5,648 | Stopped working (1=Yes) | 0.290 | (0.454) | 0.324 | (0.468) | 0.254 | (0.435) | 0.069*** |
| | 5,648 | Days stopped working | 1.943 | (4.636) | 2.105 | (4.604) | 1.773 | (4.664) | 0.332*** |
| | 1,637 | Days stopped working if >0 | 6.704 | (6.500) | 6.497 | (6.076) | 6.983 | (7.024) | -0.485 |
| **Panel C** | 5,068 | Suffered illness | 0.338 | (0.473) | 0.391 | (0.488) | 0.281 | (0.450) | 0.110*** |
| | 5,068 | Days illness | 3.483 | (6.760) | 4.169 | (7.262) | 2.748 | (6.094) | 1.421*** |
| 2010 | 1,712 | Days of illness >0 | 10.310 | (8.056) | 10.668 | (8.101) | 9.778 | (7.964) | 0.890** |
| | 5,068 | Stopped working (1=Yes) | 0.236 | (0.425) | 0.276 | (0.447) | 0.236 | (0.425) | 0.083*** |
| | 5,068 | Days stopped working (all) | 1.526 | (3.982) | 1.736 | (4.057) | 1.301 | (3.888) | 0.435*** |
| | 1,197 | Days stopped working if >0 | 6.461 | (5.938) | 6.283 | (5.569) | 6.734 | (6.460) | -0.450 |
| **Panel D** | 5,662 | Suffered illness | 0.265 | (0.441) | 0.300 | (0.459) | 0.227 | (0.419) | 0.073*** |
| | 5,662 | Days illness | 2.706 | (6.066) | 3.092 | (6.342) | 2.294 | (5.730) | -0.798*** |
| 2011 | 1,501 | Days of illness >0 | 10.207 | (7.891) | 10.294 | (7.731) | 10.083 | (8.115) | 0.210 |
| | 5,662 | Stopped working (1=Yes) | 0.202 | (0.401) | 0.228 | (0.419) | 0.174 | (0.379) | 0.053*** |
| | 5,662 | Days stopped working (all) | 1.273 | (3.701) | 1.375 | (3.606) | 1.164 | (3.798) | 0.211** |
| | 1,142 | Days stopped working if >0 | 6.311 | (6.012) | 6.045 | (5.381) | 6.681 | (6.784) | -0.636* |
| **Panel E** | 6,091 | Suffered illness | 0.236 | (0.425) | 0.285 | (0.451) | 0.184 | (0.388) | 0.100*** |
| | 6,091 | Days illness | 2.303 | (5.613) | 2.859 | (6.138) | 1.716 | (4.933) | 1.143*** |
| 2013 | 1,436 | Days of illness >0 | 9.767 | (7.793) | 10.042 | (7.760) | 9.321 | (7.832) | 0.721* |
| | 6,091 | Stopped working (1=Yes) | 0.182 | (0.386) | 0.224 | (0.417) | 0.138 | (0.345) | 0.086*** |
| | 6,091 | Days stopped working (all) | 1.220 | (3.922) | 1.500 | (4.216) | 0.925 | (3.562) | 0.575*** |
| | 1,108 | Days stopped working if >0 | 6.708 | (6.911) | 6.700 | (6.678) | 6.723 | (7.301) | -0.023 |

Standard deviations in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Risk taking health behaviours are associated with masculinity while health-promoting or improving behaviours are associated with femininity. These behaviours are taught and embraced at an early age of child growth and they contribute greatly to health gap between women and men (Evans et al., 2011). Women generally live more years than men , however, most of these years are lived with disabilities especially during old age (Carmel, 2019).

Even though we found high rate of illness consultation in women than in men, the differences were not significant as shown in Table 3.1. Significant differences were only observed in places where consultations were sought. It's important to note that some studies find no gender differences related to initial reporting of specific health conditions, and no tendency of women over-reporting especially when focusing on women and men with the same symptoms or health conditions (Macintyre et al., 1996). Furthermore, Rahman et al. (1994) consistent results on gender disparity among adults in four developing countries where women were generally disadvantaged in health, doesn't not support reporting bias as the main contributor of adult health gender differentials.

Considering health gender differences by age, several studies especially in European countries report no differences in health in boys and girls in childhood (Bisegger et al., 2005; Michel et al., 2009). In some instances, boys have increasingly more health issues in childhood compared to girls (European Commission, 2000). However, there is "*a shift gender-related health status between childhood and adolescence*" (European Commission, 2000). Michel et al. (2009) and Bisegger et al. (2005)found that health as measured in terms of health-related quality of life (HRQL) declined and was poor for girls as compared to boys in adolescents, especially after 12 years (Bisegger et al., 2005). Increasing gender differences in health at adolescent could be attributed to gender specific tasks because as children age, developmental tasks are usually gender specific (Bisegger et al., 2005). Young women in adolescent experience emotional disturbances and psychosomatic disorders (Bisegger et al., 2005) and more somatic symptoms than young men (Michel et al., 2009). Additionally, females in adolescent have poor perception of their health and older females in adolescent reported more health complaints (Bisegger et al., 2005). On the contrary, males rate their perceived health as better and report less symptoms than females (European Commission, 2000). In adulthood – ages 14 years and above, female reported worse health than males across various measures of health in all studied four developing countries (Rahman et al., 1994). Consistently, in old age, women are disadvantaged in terms of self-rated health. Carmel (2019) reported that a high proportion woman aged above 60 years reported poor self-rated health and limitations in physical functioning – for instance ADL as compared to males in several countries across different geographical locations. Similarly, older women in low- and middle-income countries have a poor self-reported health than older men, considering differences in socio-economic and demographic factors (Ng et al., 2010).

### 3.4.2 Empirical results

**Total effects of weather variables on days of illness**

As a starting point we conducted separate estimations on the effect of different extreme weather events on illness, for the different subgroups. However, we present and discuss the results of estimations with multiple weather variables in one model, in order to overcome the problem of omitted variable bias. The TPM average marginal effects estimates of weather variables on days of illness at extensive, intensive margins as well as the overall effects of the total sample, men and women sub-samples are shown in Table 3.3. In general, the logit models indicate that individuals experiencing low annual rainfall, below the long-term mean were more likely to report at least a day of illness as compared to their counterparts, holding other factors constant. Significant differences were reported in both men and women sub-samples, even though the magnitude was higher in women at – 8.3 percentage points, than in men – 6.7 percentage points. On the contrary, the GLM model shows that, among men who experienced some illnesses, low rainfall led to a significant decrease in number of days of illness by around 1.2 days. Its unclear why low rainfall led to a significant decrease in number of days of men who were sick. Nevertheless, the coefficients of the overall effect in both parts of the two-parts model for the whole subsamples of men and women were consistently positive and significant, indicating that low rainfall significantly increased days of illness in both men and women, with high effects in women of at-least one day of illness.

Correspondingly, individuals exposed to high annual temperature above the mean reported increased probability of suffering from illnesses, as compared to those not experiencing high temperature. The magnitude of effect was roughly 2 percentage points for both men and women. The temperature effect at the intensive margin for those who experienced illness was consistently insignificant, even though the overall effect was positive and highly significant in men.

Concerning the short-term weather measures, differences in rainfall and temperature experienced in the month before the interview were noted on the coefficient's signs and significance. For instance, an increase in rainfall was negatively associated with likelihood of illness in men and not in women, while temperature was positively associated with illness in both men and women. Specifically, a unit increase in log rainfall significantly reduced the probability of illness in men by 6.2 percentage points, while the effect was negative and insignificant in women. A possible explanation to the significant reduction effect of rain on illness is men is as follows; men are responsible for provision of household needs in many societies including Uganda (Morgan et al., 2017), and many rural households depend on agriculture and livestock for food and income. Therefore, increased rainfall leads to improved food production and increased income, which reduces the burden, stress and other health outcomes related to provision of household needs.

**Table 3.3**: AME results of TPM on total effect of weather on days of illness (*reduced model*)

| Variables | All sample | | | Women | | | Men | | |
|---|---|---|---|---|---|---|---|---|---|
| | Logit | GLM | Overall | Logit | GLM | Overall | Logit | GLM | Overall |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Negative rain deviation | 0.0751*** | -0.206 | 0.686*** | 0.0831*** | 0.530 | 1.035*** | 0.0672*** | -1.208** | 0.342* |
| | (0.0096) | (0.319) | (0.137) | (0.0137) | (0.417) | (0.203) | (0.0134) | (0.474) | (0.179) |
| Log monthly rain | -0.0436* | -0.126 | -0.475 | -0.0220 | -0.340 | -0.345 | -0.0615* | 0.341 | -0.511 |
| | (0.0245) | (0.776) | (0.344) | (0.0354) | (0.994) | (0.500) | (0.0336) | (1.209) | (0.461) |
| Log rainfall squared | 0.0070** | 0.013 | 0.074* | 0.0050 | 0.041 | 0.066 | 0.0085** | -0.048 | 0.070 |
| | (0.0031) | (0.099) | (0.044) | (0.0045) | (0.129) | (0.064) | (0.0043) | (0.155) | (0.059) |
| Positive temperature | 0.0226*** | 0.010 | 0.229** | 0.0206** | -0.057 | 0.189 | 0.0230** | 0.160 | 0.266** |
| | (0.0068) | (0.216) | (0.095) | (0.0098) | (0.283) | (0.142) | (0.0093) | (0.332) | (0.125) |
| Monthly temperature | 0.0435*** | -0.040 | 0.422*** | 0.0400*** | 0.235 | 0.491*** | 0.0480*** | -0.377 | 0.370** |
| | (0.0088) | (0.297) | (0.128) | (0.0124) | (0.361) | (0.182) | (0.0127) | (0.500) | (0.180) |
| Temperature squared | -0.0006*** | 0.000 | -0.006*** | -0.0006*** | -0.004 | -0.007** | -0.0007*** | 0.006 | -0.006* |
| | (0.0001) | (0.005) | (0.002) | (0.0002) | (0.006) | (0.003) | (0.0002) | (0.008) | (0.003) |
| Age | 0.004*** | 0.096*** | 0.065*** | 0.004*** | 0.100*** | 0.080*** | 0.003*** | 0.094*** | 0.053*** |
| | (0.000) | (0.009) | (0.004) | (0.000) | (0.012) | (0.006) | (0.000) | (0.015) | (0.006) |
| Education | -0.006*** | -0.051* | -0.080*** | -0.006*** | 0.008 | -0.057*** | -0.006*** | -0.115*** | -0.090*** |
| | (0.001) | (0.030) | (0.013) | (0.001) | (0.042) | (0.021) | (0.001) | (0.043) | (0.016) |
| Asset index | -0.009*** | -0.105* | -0.122*** | -0.009*** | -0.023 | -0.102*** | -0.009*** | -0.219*** | -0.146*** |
| | (0.002) | (0.054) | (0.024) | (0.003) | (0.073) | (0.036) | (0.002) | (0.082) | (0.031) |
| Water harvesting | -0.034 | 0.302 | -0.242 | 0.015 | 0.287 | 0.253 | -0.101** | -0.178 | -1.028* |
| | (0.027) | (0.845) | (0.371) | (0.036) | (1.026) | (0.523) | (0.042) | (1.492) | (0.558) |
| Irrigation use | -0.011 | 0.115 | -0.079 | -0.018 | 0.528 | 0.008 | -0.003 | -0.626 | -0.191 |
| | (0.022) | (0.738) | (0.318) | (0.033) | (0.944) | (0.470) | (0.030) | (1.135) | (0.414) |
| Treated mosquito net | -0.040*** | -0.485 | -0.547*** | -0.054*** | -0.371 | -0.678*** | -0.023 | -0.685 | -0.403** |
| | (0.011) | (0.323) | (0.145) | (0.015) | (0.412) | (0.213) | (0.015) | (0.509) | (0.196) |
| Salaried /wage | 0.067*** | -0.771*** | 0.431*** | 0.063*** | 0.005 | 0.647*** | 0.071*** | -1.528*** | 0.299* |
| | (0.009) | (0.276) | (0.128) | (0.014) | (0.372) | (0.197) | (0.012) | (0.415) | (0.163) |
| Business | 0.048*** | -0.867*** | 0.210** | 0.053*** | -0.812*** | 0.244 | 0.048*** | -0.954** | 0.217 |
| | (0.008) | (0.233) | (0.106) | (0.011) | (0.300) | (0.156) | (0.011) | (0.384) | (0.146) |
| Farming | -0.002 | -2.609*** | -0.825*** | -0.029** | -2.208*** | -1.085*** | 0.015 | -2.915*** | -0.608*** |
| | (0.009) | (0.280) | (0.124) | (0.014) | (0.390) | (0.198) | (0.011) | (0.396) | (0.150) |
| Polygamous | -0.009 | 0.243 | -0.014 | 0.002 | 0.196 | 0.087 | -0.024* | 0.309 | -0.151 |
| | (0.009) | (0.275) | (0.123) | (0.012) | (0.347) | (0.177) | (0.013) | (0.453) | (0.174) |

| | All sample | | | Women | | | Men | | |
|---|---|---|---|---|---|---|---|---|---|
| | Logit | GLM | Overall | Logit | GLM | Overall | Logit | GLM | Overall |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Divorced | 0.029** | 0.486 | 0.443*** | 0.018 | 0.367 | 0.314 | 0.049** | 0.632 | 0.638** |
| | (0.012) | (0.366) | (0.166) | (0.016) | (0.450) | (0.228) | (0.021) | (0.653) | (0.262) |
| Separated | 0.050*** | 0.653* | 0.700*** | 0.042** | 0.593 | 0.637*** | 0.063 | 1.513 | 1.006* |
| | (0.015) | (0.389) | (0.192) | (0.017) | (0.423) | (0.233) | (0.048) | (1.515) | (0.604) |
| Never married | -0.068*** | -0.086 | -0.707*** | -0.089*** | -0.276 | -1.001*** | -0.052*** | -0.032 | -0.515*** |
| | (0.009) | (0.317) | (0.137) | (0.014) | (0.416) | (0.204) | (0.014) | (0.508) | (0.189) |
| Income (1- 250000 UGX) | -0.017 | -0.024 | -0.182 | -0.008 | -0.126 | -0.124 | -0.025* | 0.137 | -0.209 |
| | (0.011) | (0.323) | (0.148) | (0.017) | (0.449) | (0.235) | (0.014) | (0.463) | (0.182) |
| Income (250,001 – 750,000) | -0.081*** | -0.548 | -0.981*** | -0.092** | -1.496 | -1.467** | -0.071*** | 0.450 | -0.578* |
| | (0.021) | (0.722) | (0.306) | (0.042) | (1.372) | (0.647) | (0.023) | (0.844) | (0.316) |
| Income (> 750,000) | -0.016 | -1.053 | -0.481 | 0.019 | 0.503 | 0.373 | -0.018 | -1.252 | -0.497 |
| | (0.040) | (1.276) | (0.570) | (0.090) | (2.425) | (1.274) | (0.042) | (1.475) | (0.572) |
| Dependency ratio | 0.000 | -0.001 | 0.000 | 0.000 | -0.002** | -0.001 | 0.000 | 0.001 | 0.000 |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.002) | (0.001) |
| Net usage | 0.061*** | -0.022 | 0.603*** | 0.069*** | 0.052 | 0.721*** | 0.051*** | -0.203 | |
| | (0.010) | (0.317) | (0.143) | (0.015) | (0.408) | (0.211) | (0.014) | (0.495) | |
| Year 2010 | 0.005 | -0.364 | -0.066 | 0.007 | 0.387 | 0.208 | 0.002 | -1.373** | -0.336 |
| | (0.011) | (0.366) | (0.161) | (0.017) | (0.477) | (0.239) | (0.016) | (0.549) | (0.210) |
| Year 2011 | -0.056*** | -0.558 | -0.737*** | -0.068*** | -0.103 | -0.726*** | -0.043*** | -1.010* | -0.685*** |
| | (0.012) | (0.382) | (0.167) | (0.017) | (0.502) | (0.249) | (0.016) | (0.574) | (0.219) |
| Year 2013 | -0.119*** | -0.957*** | -1.490*** | -0.115*** | -0.603 | -1.383*** | -0.124*** | -1.343*** | -1.562*** |
| | (0.009) | (0.295) | (0.132) | (0.014) | (0.390) | (0.197) | (0.013) | (0.446) | (0.175) |
| Sex | -0.070*** | -0.378* | -0.814*** | - | - | - | - | - | - |
| | (0.006) | (0.212) | (0.092) | | | | | | |
| N | 22,468 | 6,970 | 22,468 | 11,567 | 4,134 | 11,567 | 10,901 | 2,836 | 10,901 |

Standard errors in parentheses. Robust standard errors for GLM and TPM

*** p<0.01, ** p<0.05, * p<0.1

However, the positive and significant coefficients of the quadratic term of rainfall in men indicate that an increase in rainfall reduces the probability of illness in men until a point where further increases in rainfall results in poor health outcomes. These results imply that too much rain maybe detrimental to men health.

The effect size of temperature in the month prior to the interview on the probability of recording any illness was higher in men at 5 percentage points as compared to the women at 4 percentage points. However, the magnitude of overall effect on days of illness was high in women - around 0.5 days of illness as compared to 0.4 days in men. GLM estimations for those who reported at least a day of illness remained insignificant in men and women.

In general, even though the two-part models revealed heterogeneous effects of weather variables at both intensive and extensive margins of days of illness, most of the significant weather effects were observed in the first part and not the second part. That is, an increase in the probability of suffering illness and not an increase in number of days of illness, conditional on being sick. However, the overall effect of most weather events on the whole sample was positive and significant among men and women. The associations between weather variables (negative rain and monthly temperature), and the number of days of illness in the second part of the model was positive for women, and negative for men. Even though the positive effect in the second part was insignificant, it seems to explain the strong overall positive effect of low rainfall and temperature in women than in men. Nevertheless, the overall effect of positive temperature remained positive and significant in men and not in women.

We also conducted further analysis considering extreme weather variables with additional covariates on water quality, safety and seasonality. All other initial variables were included in the models. Results in Table 7.14 of the appendix shows that the magnitude of coefficients of extreme negative rain at the extensive margin was higher in women at 9 percentage points while the effect in men remain unchanged as shown in columns 2 and 6 respectively. However, the overall effect of extreme negative rains in women was more than double the coefficients of negative rain deviation in men. Similarly, the coefficients of extreme positive temperature were larger than coefficients of positive temperature and highly significant in women only. These results imply that extreme weather events have more adverse effects on health, than any level of negative deviation.

Controlling for gender variable in the total sample regression, men were less likely to report illness as compared to women. Other socio-economic determinants of illnesses among men and women include age, years of schooling, wealth index, use of treated mosquito net, occupation, marital status and income as shown in Table 3.3. A one-year increase in age was associated with an increase in probability of illness of about 0.4 and 0.3 percentage points in women and men respectively. The coefficients magnitude and significance levels of years of education and wealth index in the logit model were negative, and same for both genders at 1% significant level. This implied that education and wealth reduced the probability of illness. Similarly, an increase in income level had negative effects on illnesses, especially for individuals earning income of about 250,000 to 750,000 UGX. The effect size of reduction for women in this income range was higher (9.2 percentage points) than for men in the same income category (7.1%), compared to men and women receiving no income at all. While the usage of treated mosquito net was significantly correlated with reduced likelihood of illness in women by 5.4 percentage points, the effect was rather insignificant in men. The relationship between domestic rainwater harvesting and probability of illness as well as days of illness was negative and significant in men, while in women it was insignificant. Furthermore, use of irrigation reduced the likelihood of illness in both men and women, with insignificant effects. Even though improved drinking water source did not have significant effects on illness in women, treatment of drinking water through boiling and filtering regardless of the water source was significantly associated with reduced illness in women subsample and not in men. These additional results are shown in Table 7.14 of the appendix.

Heterogeneous effects of the different marriage arrangements on probability of illness across the genders were observed. For instance, men who were polygamous were less likely to report illnesses by 2.4 percentage points than those in the monogamous marriage arrangement. However, the effect was insignificant in women who were polygamously married. Similarly, men and women who were never married were less likely to report illness compared to those married monogamously – a difference of 5.2 and 9 percentage points respectively. In contrast, divorce and separation was associated with significant increase in probability of illnesses in men and women respectively by around 4-5 percentage points. With respect to the effect of occupation, there was minimal differences in coefficients and significance by gender. Men and women engaged in paid work and business reported more likelihood of illness by at-least 4 percentage points, while women engaged in household farming activities were less likely to suffer from illnesses. The effect of farming occupation was positive in men, increasing the probability of illness, even though the relationship was insignificant. The negative effect of farming on female illness can be explained as follows; farming requires physical effort, thus a form of exercise. Moreover, farmers are likely to consume a healthier diet made up of fresh vegetables, dairy and livestock products, high fibre and low-fat foods directly from their farms as opposed to fast foods, sugars, alcohol and smoking which are all risk factors for poor health (Wang et al., 2003). However, farming is also dangerous given that farmers work outdoor and are subject to accidents and hazards such as heat stress, dust, disease causing pathogens and chemicals such as pesticides (Demos et al., 2013), as well as exhaustion and stress. The positive effect in men may be due to the different roles men and women conduct on the farm. For instance, men are more responsible for activities such as pesticide application which have more health risks. Additionally, male crops are usually cash crops which requires continuous application of chemicals for pesticide or disease control.

The second part (GLM) estimations indicate that most of the covariates did not have significant effect on the number of days of illness, for sick individuals especially in the women sub-sample. Coefficients of age, years of schooling and wealth index on days of illness were significant in men, and the sign was consistent with the logit estimates. However, in women subsample, only age was significant, with an additional year increasing the number of days of illness by 0.1 days, for the women who experienced any illness. Farming was associated with reduced number of days of illness – at least 2 days in both men and women engaged in farming as compared to the base category with statistical differences at 1%. Even though men who were salaried and in business reported increased likelihood of illness, once sick, they reported a smaller number of days of illness. These results imply that those salaried or in business have financial resources, therefore able to afford and access good health care services once sick. Over the years, men experienced a smaller number of sick days as compared to the base year 2009. The negative effect was also observed in women but insignificant.

The overall effect sizes of age and salaried occupation was positive and significantly higher in women than in men. Reduction effects of an additional unit of year of schooling and asset on illness in both parts of the model was higher in men, while use of treated mosquito nets, farming, income and never married significantly reduced illnesses in women, with higher coefficient magnitudes than in men. The overall effects of covariates on men and women health are presented in columns 6 and 9 of Table 3.3.

**Direct effects of weather variables on probability of illness (Full model)**

In the previous section, we presented results on the total effect (sum of direct and indirect effect) of weather events on days of illness at extensive and intensive margins. We now present results of the direct effect of weather events at the extensive margin (only logit part), after controlling for our potential mediator variable (water collection time), in addition to other covariates. Our key variables of interest are negative rain deviation and temperature in the month before the interview reported to be significant and of higher magnitude in the previous table. ##

Results in Table 3.4 indicate similar findings of significant and positive coefficients of weather variables for the total sample, men and women sub-groups. However, the effect sizes of both weather variables reduced compared to the earlier reported figures with the introduction of our mediating variable. For instance, low rainfall below the long-term mean increased probability of illness by 8.16 percentage points and 6.69 percentage points in women and men subsamples respectively. This is the direct effect. The corresponding coefficients for total effect without mediators were 8.31 and 6.72 percentage points respectively. The coefficients for temperature were 3.85 and 4.76 percentage points for women and men respectively as compared to 4 and 4.8 percentage points earlier reported. Similarly, we find a positive and significant relationship between water collection time and probability of illness in women and men at 1% and 5% level of significance respectively. Other covariates were similar as earlier reported in terms of sign and significance level, small differences were noted on the coefficient's sizes. The results on reduced coefficients of weather variables upon introduction of the mediator variable, and the positive and significant relationship between mediator variable and probability of illness signifies the importance of water collection time in facilitating the relationship between weather events and illness. Results of the indirect effect through this pathway are presented in Table 3.7.

**Table 3.4**. AME results of logit model on effect of weather on illness (*Full model*)

| | All sample | | Women | | Men | |
|---|---|---|---|---|---|---|
| | Coefficient | Std. Err. | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Negative rain deviation | 0.0742*** | (0.0096) | 0.0816*** | (0.0137) | 0.0669*** | (0.0134) |
| Log monthly rain | -0.0415* | (0.0246) | -0.0163 | (0.0354) | -0.0631* | (0.0336) |
| Log rain squared | 0.0067** | (0.0031) | 0.0042 | (0.0045) | 0.0087** | (0.0043) |
| Positive temperature deviation | 0.0231*** | (0.0068) | 0.0214** | (0.0098) | 0.0233** | (0.0093) |
| Monthly temperature | 0.0427*** | (0.0088) | 0.0385*** | (0.0124) | 0.0476*** | (0.0127) |
| Temperature squared | -0.0006*** | (0.0001) | -0.0005*** | (0.0002) | -0.0007*** | (0.0002) |
| Water collection time | 0.0024*** | (0.0006) | 0.0029*** | (0.0007) | 0.0025** | (0.0011) |
| Age | 0.004*** | (0.000) | 0.005*** | (0.000) | 0.003*** | (0.000) |
| Education | -0.006*** | (0.001) | -0.006*** | (0.001) | -0.006*** | (0.001) |
| Asset index | -0.008*** | (0.002) | -0.007*** | (0.003) | -0.009*** | (0.002) |
| Water harvesting | -0.030 | (0.027) | 0.020 | (0.036) | -0.098** | (0.042) |
| Irrigation use | -0.011 | (0.022) | -0.016 | (0.033) | -0.003 | (0.030 |
| Treated mosquito net | -0.040*** | (0.011) | -0.055*** | (0.015) | -0.022 | (0.015) |
| Salaried/Wage | 0.065*** | (0.009) | 0.059*** | (0.014) | 0.072*** | (0.012) |
| Business | 0.047*** | (0.008) | 0.051*** | (0.011) | 0.048*** | (0.011) |
| Farming | -0.004 | (0.009) | -0.033** | (0.014) | 0.013 | (0.011) |
| Polygamous | -0.010 | (0.009) | 0.000 | (0.012) | -0.023* | (0.013) |
| Divorced | 0.029** | (0.012) | 0.019 | (0.016) | 0.046** | (0.021) |
| Separated | 0.050*** | (0.015) | 0.043** | (0.017) | 0.060 | (0.048) |
| Never married | -0.068*** | (0.009) | -0.085*** | (0.014) | -0.055*** | (0.014) |
| Income (1- 250000 UGX) | -0.016 | (0.011) | -0.005 | (0.017) | -0.025* | (0.014) |
| Income (250,001 – 750,000) | -0.080*** | (0.021) | -0.088** | (0.042) | -0.071*** | (0.023) |
| Income (> 750,000) | -0.015 | (0.039) | 0.026 | (0.089) | -0.018 | (0.042) |
| Dependency ratio | 0.000 | (0.000) | 0.000 | (0.000) | 0.000 | (0.000) |
| Net usage | 0.060*** | (0.010) | 0.069*** | (0.015) | 0.050*** | (0.014) |
| Year 2010 | 0.004 | (0.011) | 0.006 | (0.017) | 0.002 | (0.016) |
| Year 2011 | -0.057*** | (0.012) | -0.068*** | (0.017) | -0.044*** | (0.016) |
| Year 2013 | -0.119*** | (0.009) | -0.112*** | (0.014) | -0.126*** | (0.013) |
| Sex | -0.063*** | (0.007) | | | | |
| Observations | 22,468 | | 11,567 | | 10,901 | |

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

**Effect of weather events on water collection time (*path a*)**

Table 3.5 presents the results of the relationship between weather events and mediator variable (*path a*). Holding other factors constant, we find positive effects of negative rain deviation and temperature in the month before the interview on water collection time burdens. However, significant effects of both rainfall and temperature were only observed on women subsample, and not men. In the women subsample, low rainfall below the long-term mean increased water collection time by 0.6 hours while an increase in temperature in the month before interview increased water collection time by 0.4 hours respectively. These results indicate that both dry events and high temperatures increased water scarcity problem and women had to travel longer distances or spent more time at water collection points to access the resource. Detrimental effects of extreme weather events on water collection time were reported, especially among women where the effect of extreme negative rain and extreme positive temperature was almost double to any level of deviation as shown in Table 7.15 of the appendix.

Domestic water harvesting, a technology promoted in rural areas, played a substantial role in reducing time burdens in water collection activities in men by 2 hours and women by 4 hours. On the contrary, irrigation use reduced water time burdens in women only, even though the effect was insignificant. Other improved water sources were positively associated with increased time spent on water collection, especially among women as shown in Table 7.15 of the appendix.

**Table 3.5**: AME results of GLM on effect of weather on water collection time

| | All sample | | Women | | Male | |
|---|---|---|---|---|---|---|
| Variables | Coefficient (1) | Std. Err. (2) | Coefficient (3) | Std. Err. (4) | coefficient (5) | Std. Err. (6) |
| Negative rain deviation | 0.3503*** | (0.1260) | 0.5525*** | (0.1736) | 0.1926 | (0.1342) |
| Log monthly rain | -0.1917 | (0.2923) | -1.5147*** | (0.4239) | 1.2625*** | (0.3490) |
| Log rain squared | 0.0307 | (0.0380) | 0.2160*** | (0.0548) | -0.1660*** | (0.0454) |
| Positive temperature deviation | -0.2665*** | (0.0964) | -0.4949*** | (0.1351) | -0.1365 | (0.1034) |
| Monthly temperature | 0.2239** | (0.1066) | 0.3824*** | (0.1481) | 0.1564 | (0.1304) |
| Temperature squared | -0.0026 | (0.0017) | -0.0041* | (0.0024) | -0.0024 | (0.0021) |
| Age | -0.086*** | (0.005) | -0.100*** | (0.006) | -0.055*** | (0.006) |
| Education | -0.179*** | (0.014) | -0.148*** | (0.021) | -0.086*** | (0.015) |
| Asset index | -0.257*** | (0.025) | -0.671*** | (0.036) | 0.006 | (0.027) |
| Water harvesting | -2.848*** | (0.469) | -3.661*** | (0.760) | -2.114*** | (0.554) |
| Irrigation use | -0.214 | (0.370) | -0.557 | (0.422) | 0.180 | (0.412) |
| Treated mosquito net | -0.196 | (0.147) | 0.092 | (0.199) | -0.360** | (0.176) |
| Salaried/Wage | 0.515*** | (0.131) | 1.038*** | (0.191) | 0.066 | (0.165) |
| Business | -0.056 | (0.124) | 0.042 | (0.157) | -0.167 | (0.152) |
| Farming | 1.665*** | (0.151) | 2.342*** | (0.215) | 0.938*** | (0.146) |
| Polygamous | 0.096 | (0.139) | 0.601*** | (0.179) | -0.743*** | (0.215) |
| Divorced | 0.848*** | (0.170) | 0.036 | (0.232) | 1.639*** | (0.225) |
| Separated | 0.439** | (0.187) | -0.464* | (0.249) | 1.981*** | (0.417) |
| Never married | 0.463*** | (0.134) | -1.228*** | (0.165) | 0.910*** | (0.147) |
| Income (1- 250000 UGX) | -0.410*** | (0.157) | -0.725*** | (0.231) | -0.054 | (0.184) |
| Income (250,001 – 750,000) | -0.587 | (0.397) | -1.636** | (0.686) | -0.309 | (0.321) |
| Income (> 750,000) | -0.766 | (0.719) | -3.074* | (1.795) | -0.254 | (0.513) |
| Dependency ratio | -0.001** | (0.000) | -0.001 | (0.001) | -0.001 | (0.001) |
| Net usage | 0.465*** | (0.143) | 0.453** | (0.199) | 0.424** | (0.167) |
| Year 2010 | 0.328** | (0.154) | 0.409* | (0.226) | 0.081 | (0.163) |
| Year 2011 | 0.375** | (0.162) | 0.279 | (0.222) | 0.393** | (0.181) |
| Year 2013 | 0.535*** | (0.140) | -0.404** | (0.196) | 1.066*** | (0.157) |
| Sex | -2.607*** | (0.105) | | | | |
| N | 22,468 | | 11,567 | | 10,901 | |

Standard errors in parentheses. Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

**Time spent on water collection and probability of illness (*path b*)**

In Table 3.4, we presented results of weather events on illness, controlling for mediator variables. Table 3.6 presents the relationship between water collection time and probability of illness, without controlling for weather events. Other covariates remain as earlier defined. In both men and women subsamples, results indicate that an increase in water collection time had positive and significant effects on likelihood of illness. In women, one hour increase in water collection time increased propensity of illness by 0.32 percentage points. In men, the probability of illness due to water collection time was 0.26 percentage points. This effect was significant at 1% and 5 % level of significance in women and men respectively.

**Table 3.6**: AME results of logit on relationship between water collection time and illness

| | All sample | | Women | | Men | |
|---|---|---|---|---|---|---|
| Variables | Coefficient (1) | Std. Err. (2) | Coefficient (3) | Std. Err. (4) | Coefficient (5) | Std. Err. (6) |
| Water collection time | 0.0027*** | (0.0006) | 0.0032*** | (0.0007) | 0.0026** | (0.0012) |
| Age | 0.004*** | (0.000) | 0.005*** | (0.000) | 0.003*** | (0.000) |
| Education | -0.006*** | (0.001) | -0.005*** | (0.001) | -0.006*** | (0.001) |
| Asset index | -0.007*** | (0.002) | -0.006** | (0.003) | -0.008*** | (0.002) |
| Water harvesting | -0.041 | (0.027) | 0.010 | (0.036) | -0.110*** | (0.042) |
| Irrigation use | 0.006 | (0.022) | 0.003 | (0.033) | 0.010 | (0.030) |
| Treated mosquito net | -0.040*** | (0.011) | -0.054*** | (0.015) | -0.023 | (0.015) |
| Salaried/Wage | 0.066*** | (0.009) | 0.057*** | (0.014) | 0.075*** | (0.012) |
| Business | 0.048*** | (0.008) | 0.052*** | (0.011) | 0.050*** | (0.011) |
| Farming | -0.005 | (0.009) | -0.036*** | (0.014) | 0.015 | (0.011) |
| Polygamous | -0.010 | (0.009) | 0.000 | (0.012) | -0.023* | (0.013) |
| Divorced | 0.036*** | (0.012) | 0.025 | (0.016) | 0.054*** | (0.021) |
| Separated | 0.053*** | (0.015) | 0.046*** | (0.017) | 0.058 | (0.048) |
| Never married | -0.067*** | (0.009) | -0.085*** | (0.014) | -0.053*** | (0.014) |
| Income (1- 250000 UGX) | -0.015 | (0.011) | -0.002 | (0.017) | -0.025* | (0.014) |
| Income (250,001 – 750,000) | -0.077*** | (0.021) | -0.079* | (0.042) | -0.070*** | (0.023) |
| Income (> 750,000) | -0.011 | (0.040) | 0.033 | (0.090) | -0.016 | (0.042) |
| Dependency ratio | 0.000 | (0.000) | 0.000 | (0.000) | 0.000 | (0.000) |
| Net usage | 0.063*** | (0.010) | 0.071*** | (0.015) | 0.052*** | (0.014) |
| Year 2010 | -0.068*** | (0.008) | -0.071*** | (0.012) | -0.065*** | (0.011) |
| Year 2011 | -0.134*** | (0.008) | -0.152*** | (0.012) | -0.113*** | (0.011) |
| Year 2013 | -0.160*** | (0.008) | -0.157*** | (0.012) | -0.162*** | (0.011) |
| Sex | -0.063*** | (0.007) | | | | |
| Observations | 22,469 | | 11,568 | | 10,901 | |

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

**Indirect effects of weather variables on probability of illness, through water collection time**

So far, we have established the total and direct effects of our key weather variables (negative rainfall deviation, and temperature prior to interview month) on probability of illness (*paths c and c'*), effect of weather events on water collection time (*path a*), and effect of water collection time on probability of illness (*path b*). In order to quantify the indirect effect of key weather events on probability of illness through the water collection time, we report KHB estimates as recommended by Kohler et al (2011). This method also enabled us to test the success of mediation process and provided the significance levels of indirect effect coefficients, reported for logit estimates. The coefficients on the weather variables in the reduced model and full models indicate total and direct effects respectively, while the difference between these two coefficients is the indirect effect, mediated by water collection time as shown in Table 3.7.

For women subsample, water collection time mediated the relationship between low rainfall below the long-term mean and probability of illness as well as the relationship between temperature in the month before the interview and likelihood of illness. Exposure to low rainfall led to more time burdens, which translated into a higher probability of illness in women of 0.15 percentage points. Similarly, an increase in temperature, increased water collection time, which led to a higher likelihood of illness by 0.12 percentage points as shown in columns 7 of panel A and panel B of Table 3.7 respectively. The mediation effect of water collection was significant for both rainfall-illness relationship as well as for temperature-illness. The KHB ape estimates do not indicate the standard error and significance levels, therefore we rely on KHB logit estimates. The confounding ratio in women indicate that the total effect of low rainfall and temperature was 1.02 and 1.03 larger than the direct effect of these key variables respectively while the mediation percentages reveal that 2% and 3% of the total effect were due to water time burdens. These coefficient sizes indicate that the effect of temperature was mediated stronger by water collection time, than low rainfall.

For men, water collection time mediated the relationship between low rainfall and probability of illness (0.55 percent of the total effect) and relationship between high temperature and illness (0.81 percent of the total effect). In probability terms, occurrence of dry events, and increase in temperature led to more time allocation on water collection, which increased the likelihood of illness by 0.04 percentage points. However, the mediation effect for water collection time in the relationship between weather events and illness was insignificant.

**Summary of mediation analysis**

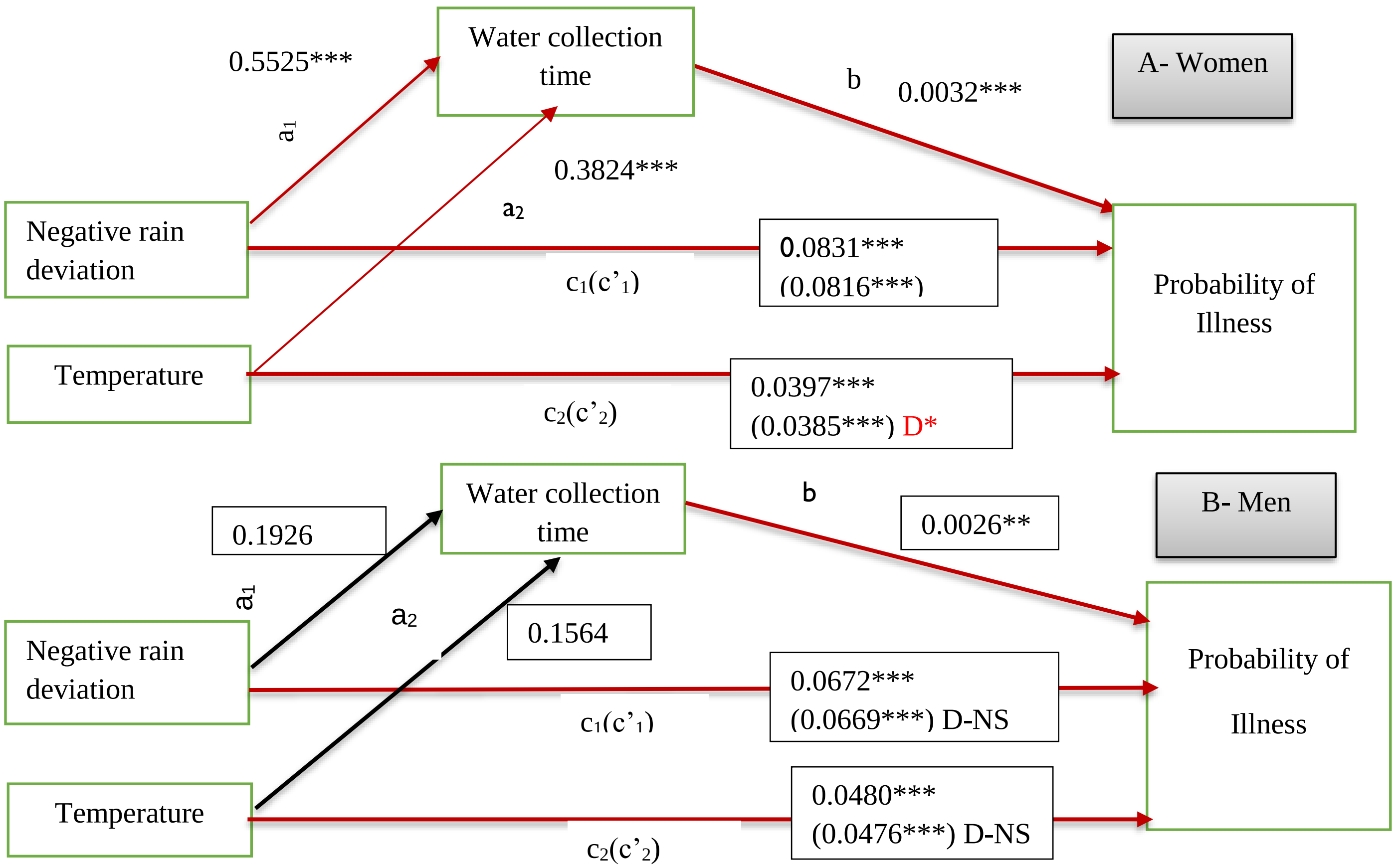


**Figure 3.6:** Path diagram showing the total, direct and indirect effects of weather on illness in women (A) and men (B), mediated by water collection time[23].

The diagrammatic summary of the relationship between the different components of the mediation process in women and men are presented in Figure 3.6 and Figure 3.7 respectively. In women, all the coefficients on the different paths (a, b and c) were significant, including the indirect effect (difference in path c coefficients after introduction of mediator variables), especially on relationships between negative rainfall deviation and illness. In men, paths b and c were significant while path a's and the difference in paths c's were insignificant. In conclusion, our results support fully the mediation process of water collection time in the relationship between low rainfall and illness in women, while mediation process in men is partially supported.

[23] Notes, the arrows show the direction of the effects. The red arrows show significant paths while black arrows show the insignificant paths. The coefficients in brackets represents the effects after introduction of the mediator variable.

**Table 3.7:** KHB decomposition results of direct, indirect and total effects of selected weather variables on illness, through water collection time pathway

| | **All Sample** | | | | **Women** | | | | **Men** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Logit estimates | | Average partial effects | | Logit estimates | | Average partial effects | | Logit estimates | | Average partial effects | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Variables | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| **Panel A** | | | | | | | | | | | | |
| **Negative rainfall deviation** | | | | | | | | | | | | |
| Reduced model[24] | 0.3873*** | (0.0496) | 0.0750*** | (0.0096) | 0.4003*** | (0.0661) | 0.0831*** | (0.0137) | 0.3775*** | (0.0756) | 0.0672*** | (0.0134) |
| Full model | 0.3830*** | (0.0496) | 0.0742*** | (0.0096) | 0.3932*** | (0.0661) | 0.0816*** | (0.0137) | 0.3754*** | (0.0756) | 0.0669*** | (0.0134) |
| Difference (Indirect effect) | 0.0043** | (0.0020) | 0.0008 | . | 0.0071** | (0.0036) | 0.0015 | . | 0.0021 | (0.0022) | 0.0004 | . |
| Confounding ratio | 1.0112 | | 1.0112 | | 1.0180 | | 1.0180 | | 1.0055 | | 1.0055 | |
| Mediation percentage | 1.11 | | 1.11 | | 1.78 | | 1.78 | | 0.55 | | 0.55 | |
| Panel B | | | | | | | | | | | | |
| **Month temperature** | | | | | | | | | | | | |
| Reduced model | 0.2233*** | (0.0456) | 0.0433*** | (0.0088) | 0.1912*** | (0.0596) | 0.0397*** | (0.0123) | 0.2693*** | (0.0716) | 0.0480*** | (0.0127) |
| Full model | 0.2202*** | (0.0456) | 0.0427*** | (0.0088) | 0.1856*** | (0.0596) | 0.0385*** | (0.0124) | 0.2672*** | (0.0716) | 0.0476*** | (0.0127) |
| Difference | 0.0031 | (0.0019) | 0.0006 | . | 0.0056* | (0.0034) | 0.0012 | . | 0.0022 | (0.0023) | 0.0004 | . |
| Confounding ratio | 1.0138 | | 1.0138 | | 1.0304 | | 1.0304 | | 1.0081 | | 1.0081 | |
| Mediation percentage | 1.37 | | 1.37 | | 2.95 | | 2.95 | | 0.81 | | 0.81 | |
| Other variables | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| N | 22468 | | 22468 | | 11567 | | 11567 | | 10901 | | 10901 | |

[24] The reduced model measures the total effect, the full model measures direct effect and the difference is the indirect effect.

**Effect of weather variables on work days lost due to the illness**

Table 3.8 presents two-part estimation results on the gender differentiated effects of weather variables on days an individual stopped working due to the illness. Just like in the case of days of illnesses earlier reported, holding other factors constant, women and men experiencing low rainfall below the long-term mean were more likely to report illness related work absences by at least 5 percentage points, than women and men who experienced did not experience low rainfall, as shown in columns 1, 4 and 7. However, the magnitude of effect of long-term low rainfall was higher in women than in men, with a difference of about 3 percentage points. Among those men and women who took time off their usual work due to illness, low rainfall significantly reduced the number of days absent from the work. The overall effects of low rainfall on both parts of the model for the whole sample were positive and significant in both groups, with higher effects in women.

Conditional on experiencing at least a day of restricted work, gender differences on the effect of rainfall in the month before the interview on work absences were noted. For instance, while the coefficient of increased rainfall was negative in men, women lost an additional 1.3 work days on average in response to the high rainfall as shown in column 5, even though the effect was insignificant. However, the overall effect of an increase in rainfall in the month prior to the interview was positive and significant in women – an additional 0.6 days of illness, while in men the coefficient was insignificant and negative.

Exposure to positive temperature variations increased the probability of work days lost significantly by about 1.3 percentage points for the total sample. The magnitude of effect on women was significant and almost double the effect observed on men (1.6 versus 0.8 percentage points), which was insignificant in men. On the contrary, the effect size of the short-term temperature on likelihood of absence from work was lower and insignificant in women, whereas in men it was significant at 1% level of significance. That is, an additional $1^0$C increase in temperature in the month prior to the interview increased the probability of absence from work due to illness by about 4 percentage points in men. These results indicate that women health respond more to long-term temperature changes while men to short-term temperature changes.

Results in columns 6 and 9 reveal gender differentiated overall effect of the weather variables on the work days lost due to illness, considering both the effects in the first part and second part. For instance, all the rainfall variables were positively and significantly associated with work days lost in women, while in men the significance differences were only observed on the negative rain deviation variable with less magnitudes as compared to women. The overall effect of positive temperature deviation was insignificant in both groups, while temperature in the month prior to the interview was significant and positive in men only.

**Table 3.8**: Effect of weather events on days stopped working – AME of the TPM

| Variables | Total sample | | | Women | | | Men | | |
|---|---|---|---|---|---|---|---|---|---|
| | Logit | GLM | Overall | Logit | GLM | Overall | Logit | GLM | Overall |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Negative rain | 0.068*** | -0.850*** | 0.250*** | 0.081*** | -0.866** | 0.285** | 0.055*** | -0.779* | 0.221** |
| | (0.009) | (0.283) | (0.085) | (0.013) | (0.367) | (0.124) | (0.012) | (0.425) | (0.113) |
| Log monthly rain | 0.020 | 0.359 | 0.211 | 0.037 | 1.256 | 0.560* | 0.004 | -1.285 | -0.214 |
| | (0.023) | (0.658) | (0.214) | (0.034) | (0.797) | (0.303) | (0.032) | (1.130) | (0.302) |
| Log rain squared | -0.002 | -0.039 | -0.020 | -0.004 | -0.153 | -0.062 | 0.000 | 0.161 | 0.030 |
| | (0.003) | (0.085) | (0.027) | (0.004) | (0.104) | (0.039) | (0.004) | (0.145) | (0.039) |
| Positive temperature | 0.013** | -0.008 | 0.081 | 0.016** | -0.045 | 0.091 | 0.008 | 0.082 | 0.069 |
| | (0.006) | (0.192) | (0.059) | (0.009) | (0.239) | (0.085) | (0.008) | (0.309) | (0.081) |
| Monthly temperature | 0.027*** | -0.123 | 0.145* | 0.019 | -0.166 | 0.076 | 0.038*** | 0.034 | 0.258** |
| | (0.008) | (0.249) | (0.078) | (0.012) | (0.289) | (0.106) | (0.012) | (0.445) | (0.116) |
| Temperature squared | 0.000*** | 0.002 | -0.002* | 0.000 | 0.003 | -0.001 | -0.001*** | 0.000 | -0.004** |
| | (0.000) | (0.004) | (0.001) | (0.000) | (0.005) | (0.002) | (0.000) | (0.007) | (0.002) |
| Other factors | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mediator variable | No | No | No | No | No | No | No | No | No |
| Observations | 22,468 | 5,083 | 22,468 | 11,567 | 3,027 | 11,567 | 10,901 | 2,056 | 10,901 |

Standard errors in parentheses. Robust standard errors for GLM and TPM

*** p<0.01, ** p<0.05, * p<0.1

With regards to the determinants of the work days lost, controlled in Table 3. 8 are similar to those reported for days of illness in Table 3.3 with minimal differences on effect sizes. Age, years of schooling, assets, salaried, polygamous, never married, domestic water harvesting and income were significantly associated with probability of work days lost in men[25]. The same factors were significant in women except polygamous marriage and water harvesting. In addition, farming was significant in women in both parts while use of treated mosquito net, business and income were significant in the second part as well as for the overall effect and not in the first part.

**Robustness check: HNBM estimates on days of illness and work days lost.**

Since the outcome variable was a count, we repeated the two-part estimation using the hurdle count model as shown in Table 7.16 of the appendix. We were unable to derive the overall effect using the hurdle count model; therefore, we compare the first- and second-part results estimates, and use negative binomial estimates for the whole sample to discuss the overall effect. Results of the effect of weather events on days of illness in the first part of the model (logit) were similar to those reported in Table 3.3, while results in the second part and overall effect differed by effect size only. The effect sign and significance levels were similar to those earlier reported and the magnitude of overall effect for negative binomial model in Table 7.16 was larger than estimates in Table 3.3. For instance, the overall effect of negative rainfall and temperature prior to the interview was 1.36 and 0.56 days of illness in women respectively, while the corresponding estimates in two parts model was 1.04 and 0.49 days. In men, the overall effect was 0.56 and 0.49 days for negbin model while for two-part model the overall effect was 0.34 and 0.37 for low rainfall and temperature respectively.

Similarly, logit parameter marginal effects estimate for the hurdle negative binomial model in Table 7.16, Panel B, for the missed work days were similar to those in the two parts model in Table 3.8, as well as the coefficients for the TNB and GLM, conditional on reporting any work days lost. However, the overall effects of TPM model were of lower magnitude as compared to the negbin estimates for negative rain. The estimates were 0.49 and 0.30 work days lost in women and men respectively for negbin model while the overall effect for TPM was 0.29 and 0.22 work days lost respectively as shown in Table 7.16 and Table 3.8.

The other weather variables remained insignificant in the truncated part of the model, except the monthly rainfall variable in women. An increase in rainfall in the month before interview increased the number of days women were unable to conduct their usual activities by 1.3 days as shown in Table 7.16.

**Relationships between health care and days of illness or work days lost**

Results in Table 3.9 illustrates the association between different health care services and sick days, controlling for weather and other socio-economic covariates on the subsample of individuals who were sick and sought consultation. Gender based differences on the effect of health care services

[25] These results are not shown in the table due to space limitations

were noted. Most of the health care variables were significant showing evidence of the importance of health care services on health outcomes at the intensive margin (number of days of illness), especially in men. Distance to the health facility was positively associated with increased number of days of illness in both men and women. Specifically, an additional increase in distance by 1 km increased the number of days of illness in men by 0.14 and in women by 0.11 at 1% significance level. The results were consistent across the different regression models. Men who sought treatment in the government hospitals or health centres recorded significantly a smaller number of days of illness (1.9 days) than those who sought from base category (other healthcare centres). The coefficient sizes were higher for private hospitals/doctor than government health centres in men.

In women, the effect of government hospitals and private health care were insignificant, even though the sign was negative as expected. Access to pharmacy had significant and negative effects on the number of days of illness in both men and women, with higher effect sizes of approximately 4 days, and the results were statistically significant at 1% level.

The discrepancy in coefficient sizes and significance levels among men and women who sought treatment from different health care arrangements could be possibly due to gender discrimination and biases by health care providers. These gender biases dictate the interactions between the health providers and the patient, thus impacting on diagnosis and treatment outcomes, especially women who are socio-economically disadvantaged (Govender & Penn-Kekana, 2008). In Uganda, some health workers have negative attitude, rude and abuse women especially while seeking health care during certain vulnerable periods (Morgan et al., 2017).

With reference to the relationship between health care services and number of days absent from work, results in Table 3.10 indicate significant effects in both men and men. As reported earlier, distance to the health facility, government hospital, private hospital and pharmacy had significant effects in men with expected signs, even though the effect sizes of these variables were a bit lower than those reported for days of illness. Moreover, unlike for the number of sick days where there were no significant differences of private and government hospital in women, the number of work days missed by women who sought consultations from the specified health care services were significantly lower by one day. Women who sought health care services from pharmacies missed significantly less days of work- a reduction of about 3 days, as compared to those who sought health assistance from the other health care (base category). The effect in men was greater – a reduction in work days loss of nearly 4 days. Additional rainfall significantly increased the work days lost in women, while in men the effect was insignificant.

**Table 3.9**: Association between health care services and number of days of illness

| Variables | All GLM | All TNB | All NB | Women GLM | Women TNB | Women NB | Men GLM | Men TNB | Men NB |
|---|---|---|---|---|---|---|---|---|---|
| Distance to health | 0.125*** | 0.123*** | 0.122*** | 0.114*** | 0.112*** | 0.111*** | 0.142*** | 0.138*** | 0.137*** |
| | (0.010) | (0.011) | (0.010) | (0.012) | (0.013) | (0.013) | (0.019) | (0.018) | (0.017) |
| Government hospital | -1.136*** | -1.152*** | -1.136*** | -0.673 | -0.692 | -0.686 | -1.837*** | -1.866*** | -1.835*** |
| | (0.440) | (0.412) | (0.396) | (0.555) | (0.527) | (0.508) | (0.707) | (0.660) | (0.631) |
| Private hospital/doctor | -1.128*** | -1.161*** | -1.147*** | -0.601 | -0.635 | -0.632 | -1.979*** | -2.023*** | -1.991*** |
| | (0.440) | (0.412) | (0.395) | (0.560) | (0.532) | (0.513) | (0.697) | (0.649) | (0.621) |
| Pharmacy or drug shop | -3.215*** | -3.291*** | -3.212*** | -2.881*** | -2.954*** | -2.885*** | -3.765*** | -3.859*** | -3.764*** |
| | (0.453) | (0.430) | (0.413) | (0.579) | (0.559) | (0.538) | (0.713) | (0.675) | (0.644) |
| Negative rainfall deviation | -0.460 | -0.451 | -0.434 | 0.213 | 0.227 | 0.223 | -1.318*** | -1.336*** | -1.293*** |
| | (0.329) | (0.323) | (0.310) | (0.427) | (0.416) | (0.400) | (0.492) | (0.512) | (0.488) |
| Log month rain | -0.237 | -0.247 | -0.244 | -1.077 | -1.103 | -1.084 | 1.144 | 1.180 | 1.146 |
| | (0.788) | (0.760) | (0.728) | (1.024) | (0.984) | (0.948) | (1.198) | (1.190) | (1.133) |
| Log rain squared | 0.034 | 0.035 | 0.035 | 0.146 | 0.150 | 0.147 | -0.151 | -0.156 | -0.151 |
| | (0.102) | (0.098) | (0.094) | (0.132) | (0.127) | (0.123) | (0.154) | (0.154) | (0.147) |
| Positive temperature | -0.103 | -0.115 | -0.115 | 0.019 | 0.006 | 0.004 | -0.192 | -0.215 | -0.214 |
| | (0.222) | (0.219) | (0.210) | (0.290) | (0.287) | (0.276) | (0.342) | (0.340) | (0.324) |
| Month temperature | 0.307 | 0.339 | 0.338 | 0.453 | 0.482 | 0.476 | 0.197 | 0.214 | 0.212 |
| | (0.311) | (0.292) | (0.280) | (0.385) | (0.367) | (0.353) | (0.508) | (0.482) | (0.459) |
| Temperature squared | -0.005 | -0.005 | -0.005 | -0.007 | -0.007 | -0.007 | -0.003 | -0.003 | -0.003 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.008) | (0.008) | (0.007) |
| Sex | -0.248 | -0.239 | -0.227 | | | | | | |
| | (0.219) | (0.208) | (0.200) | | | | | | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mediator variables | No | No | No | No | No | No | No | No | No |
| N | 6,122 | 6,122 | 6,122 | 3,639 | 3,639 | 3,639 | 2,483 | 2,483 | 2,483 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 3.10**: Relationship between health care services and work days lost

| | All | | | Women | | | Men | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | GLM | TNB | NB | GLM | TNB | NB | GLM | TNB | NB |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Distance to health facility | 0.092*** | 0.090*** | 0.082*** | 0.090*** | 0.088*** | 0.078*** | 0.092*** | 0.090*** | 0.086*** |
| | (0.009) | (0.009) | (0.009) | (0.011) | (0.010) | (0.011) | (0.015) | (0.015) | (0.015) |
| Government hospital | -1.209*** | -1.239*** | -1.204*** | -0.919** | -0.933** | -0.998** | -1.710*** | -1.763*** | -1.542*** |
| | (0.359) | (0.327) | (0.322) | (0.456) | (0.399) | (0.397) | (0.582) | (0.563) | (0.544) |
| Private hospital/doctor | -1.176*** | -1.219*** | -1.132*** | -0.847* | -0.873** | -0.829** | -1.807*** | -1.873*** | -1.672*** |
| | (0.358) | (0.326) | (0.320) | (0.457) | (0.402) | (0.399) | (0.571) | (0.554) | (0.535) |
| Pharmacy or drug shop | -3.033*** | -3.211*** | -3.256*** | -2.722*** | -2.883*** | -2.982*** | -3.544*** | -3.749*** | -3.713*** |
| | (0.381) | (0.353) | (0.342) | (0.488) | (0.437) | (0.428) | (0.606) | (0.593) | (0.567) |
| Negative rainfall deviation | -0.875*** | -0.926*** | -0.373 | -0.838** | -0.890*** | -0.225 | -0.847** | -0.908* | -0.528 |
| | (0.279) | (0.273) | (0.258) | (0.356) | (0.333) | (0.320) | (0.426) | (0.469) | (0.430) |
| Log month rain | 0.579 | 0.614 | 1.769*** | 1.231 | 1.267 | 1.983*** | -0.802 | -0.754 | 1.285 |
| | (0.650) | (0.661) | (0.588) | (0.800) | (0.800) | (0.732) | (1.145) | (1.153) | (0.977) |
| Log rain squared | -0.070 | -0.075 | -0.225*** | -0.152 | -0.156 | -0.254*** | 0.091 | 0.084 | -0.172 |
| | (0.085) | (0.085) | (0.076) | (0.105) | (0.103) | (0.095) | (0.147) | (0.147) | (0.126) |
| Positive temperature deviation | -0.184 | -0.195 | -0.251 | -0.128 | -0.132 | -0.082 | -0.240 | -0.257 | -0.473* |
| | (0.187) | (0.182) | (0.172) | (0.233) | (0.226) | (0.216) | (0.307) | (0.306) | (0.282) |
| Month temperature | 0.176 | 0.197 | 0.179 | 0.000 | 0.007 | -0.076 | 0.537 | 0.581 | 0.722* |
| | (0.248) | (0.244) | (0.227) | (0.298) | (0.287) | (0.276) | (0.410) | (0.450) | (0.399) |
| Temperature squared | -0.002 | -0.002 | -0.003 | 0.001 | 0.001 | 0.001 | -0.008 | -0.009 | -0.013** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.004) | (0.007) | (0.007) | (0.006) |
| Sex | 0.458** | 0.491*** | 0.423*** | | | | | | |
| | (0.182) | (0.174) | (0.163) | | | | | | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mediator variables | No | No | No | No | No | No | No | No | No |
| N | 4,632 | 4,632 | 6,122 | 2,776 | 2,776 | 3,639 | 1,856 | 1,856 | 2,483 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Multivariate decomposition results**

Table 3.11 presents multivariate results for logistic and negative binomial gender health gap decomposition. Generally, the overall decomposition reveals that most of the differences in the health status in terms of prevalence of illness and work days lost between women and men were due to coefficients or differences in effects, thus unexplained. Differences in observed endowments or characteristics between men and women only explained 27% and 34% of the gender health gap at the extensive margin (illness and stop working) as illustrated in columns 2 and 4 respectively.

Focusing on the explained component part of the detailed decomposition, results show that all the weather variables played significant roles in explaining the gender health gap in terms of probability of suffering an illness, except rainfall in the month prior to the interview. However, the magnitude of contribution of these weather variables to the overall explained component of the gap was minimal. For instance, temperature in the month prior to the interview month only contributed to 4.9%. Specifically, women-men health differences in terms of likelihood of suffering from illness would have decreased by at least 4% if women and men were exposed to the same temperatures' distribution regimes. All the rest of the weather variables contribution to the total explained gap of 27% was less than 1%.

With regards to contribution of the other individual and household socioeconomic characteristics to gender health inequality, most of the gender health differences on suffering illness was explained by age which significantly accounted for 5.7% of the total explained gap, years of schooling (9.7%) and marital status- never married, which contributed to the highest proportion of the gap (16.5%). Given the positive effect of these variables on women-men health gap, the results imply that the inequalities in health status between women and men would be eliminated or narrowed if all individuals of both gender groups were of the same age, similar marital status arrangements and similar education levels. For instance, if women had the same marital arrangements (never married) as men, the gender health inequalities would have reduced greatly by about 16.5%. Similarly, wealth index and income level of between 250,000 to 750,000 UGX were significant in explaining the gap in illness between the women and men, even though the magnitude was small. On the other hand, differences in the occupation status were significant in narrowing the health gap at the extensive margin, especially the gender differences in the paid work, accounting for -8% of the gap in illness. Other covariates that were significant in explaining gender health differentials, though with minimal contributions in terms of percentage include; use of treated mosquito nets and the different year dummies.

Only long-term weather measures (negative rain deviation and positive temperature deviation) differences contributed significantly to the gender health gap, at the extensive margin in terms of probability of work days lost. The magnitude of contribution of temperature exposure differences in women and men was higher than the rest of the weather variables (2.9%), even though the effect was insignificant. Differences in age, years of schooling and marital status also contributed significantly to increasing the gap in terms of work days lost. For instance, the women-men gap in terms of the likelihood of missed work days is expected to reduce by 5%, 13% and 18% if age, years of education and marital status (never married) are equalized for the both groups. Wealth differences explained 0.2% of the gap while all occupation categories (paid work and farming) explained a significant proportion of the gap of about -8%. Different income categories did not contribute significantly to the observed gender gap on work related abseentism.

For differences in the number days of illness and work days lost, the proportion of the overall health gap attributable to differences in characteristics was relatively higher to that reported at the extensive margin, more so on the number of work days lost. However, approximately 57-70 % of the gap was largely due to the coefficient's effects and could not be explained. Columns 5,6,7 and 8 of Table 3.11 presents both the overall and detailed decomposition results where differences in negative rainfall deviation and temperature in the month prior to the interview contributed significantly to the compositional effects on days of illness, while only negative rainfall deviation significantly contributed to the number of work days lost due to the illness. The proportion of health gap explained by the weather variables was however minimal, with temperature contributing the highest at around 5% on number of days of illness.

Just like at the extensive margin, over half of gender health inequalities (both the number of days of illness and days stopped working) due to differences in characteristics were explained by never married category of marital status. That is, the women-men gap in number of days and work days lost would have been narrowed by 19 and 27% respectively if men and women were in similar arrangements (never married). Moreover, if women age and education level distributions were equal to those of men, the women-men health gap in terms of the number of days of illness would be expected to cumulatively reduce by 17%, while the number of work days lost due to illness would reduce cumulatively by up-to 22%. Farming occupation and paid work significantly contributed to reducing the gap by -19%, while differences in treated nets were found to explain reduce the gender health gap in a range between -3 and -4% as shown in column 6 and 7.

Controlling for health seeking behaviours in the decomposition analysis and other factors, results in Figure 3.7 and Table 7.17 indicate that the proportion of gender health inequalities explained by the endowment component increased significantly. In particular, the explained health gap in the number of days of illness doubled to 57% as compared to 27% without health care variables. This reveals the importance of health care services at the intensive margin. Gender differentials in terms of distance to the health explains a considerable magnitude of about 14% of the health gap, access to pharmacy or drug shop accounts for 21% while government hospital and private hospital explains 7% and -4% respectively.

**Table 3.11**: Multivariate decomposition of women-men gap on illnesses and work days lost

| VARIABLES | Logistic | | | | Negative binomial | | | |
|---|---|---|---|---|---|---|---|---|
| | Suffered illness (dummy) | | Stopped working (dummy) | | Days illness (number) | | Days stopped working (number) | |
| | Coefficients | Percent | Coefficients | Percent | Coefficients | Percent | Coefficients | Percent |
| **Overall decomposition** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Characteristics (E) – Explained | 0.0250*** | 27.121 | 0.0237*** | 34.349 | 0.3306*** | 29.274 | 0.1634*** | 42.595 |
| | (0.0033) | | (0.0031) | | (0.0760) | | (0.0396) | |
| Coefficients (C) – Unexplained | 0.0673*** | 72.879 | 0.0453*** | 65.651 | 0.7987*** | 70.726 | 0.2202** | 57.405 |
| | (0.0089) | | (0.0078) | | (0.1761) | | (0.0937) | |
| Raw difference | 0.0923*** | 100 | 0.0690*** | 100 | 1.1292*** | 100 | 0.3836*** | 100 |
| | (0.0084) | | (0.0073) | | (0.1709) | | (0.0912) | |
| **Detailed decomposition (E)** | | | | | | | | |
| Negative rainfall deviation | -0.0006*** | -0.666 | -0.0006*** | -0.848 | -0.0089*** | -0.784 | -0.0030*** | -0.785 |
| | (0.0001) | | (0.0001) | | (0.0022) | | (0.0010) | |
| Log month rain | 0.0003 | 0.347 | -0.0005 | -0.759 | 0.0035 | 0.312 | -0.0068 | -1.783 |
| | (0.0005) | | (0.0005) | | (0.0095) | | (0.0046) | |
| Log rain squared | -0.0006 | -0.692 | 0.0004 | 0.639 | -0.0075 | -0.659 | 0.0065 | 1.683 |
| | (0.0006) | | (0.0005) | | (0.0107) | | (0.0052) | |
| Positive temperature deviation | -0.0001** | -0.077 | -0.0001* | -0.080 | -0.0005 | -0.044 | -0.0002 | -0.039 |
| | (0.0000) | | (0.0000) | | (0.0006) | | (0.0003) | |
| Month temperature | 0.0045*** | 4.892 | 0.0021 | 3.023 | 0.0552** | 4.888 | 0.0120 | 3.134 |
| | (0.0014) | | (0.0013) | | (0.0261) | | (0.0127) | |
| Temperature squared | -0.0042*** | -4.574 | -0.0020 | -2.937 | -0.0538* | -4.767 | -0.0109 | -2.838 |
| | (0.0015) | | (0.0014) | | (0.0279) | | (0.0136) | |
| Age | 0.0053*** | 5.744 | 0.0036*** | 5.198 | 0.0880*** | 7.791 | 0.0352*** | 9.179 |
| | (0.0005) | | (0.0005) | | (0.0123) | | (0.0055) | |
| Education | 0.0089*** | 9.680 | 0.0090*** | 13.023 | 0.1021** | 9.04 | 0.0477** | 12.439 |
| | (0.0022) | | (0.0021) | | (0.0456) | | (0.0224) | |
| Asset index | 0.0002*** | 0.241 | 0.0001** | 0.164 | 0.0023** | 0.208 | 0.0010* | 0.258 |
| | (0.0001) | | (0.0001) | | (0.0011) | | (0.0006) | |
| Water harvesting | 0.0000 | 0.005 | 0.0000 | 0.012 | 0.0001 | 0.010 | 0.0001 | 0.026 |
| | (0.0000) | | (0.0000) | | (0.0002) | | (0.0001) | |
| Irrigation use | 0.0000 | 0.015 | 0.0000 | 0.026 | 0.0001 | 0.013 | -0.0000 | -0.011 |
| | (0.0000) | | (0.0000) | | (0.0005) | | (0.0002) | |
| Treated mosquito net | -0.0031*** | -3.305 | -0.0007 | -1.020 | -0.0318* | -2.818 | -0.0142* | -3.712 |
| | (0.0009) | | (0.0008) | | (0.0168) | | (0.0083) | |
| Salaried /wage | -0.0076*** | -8.182 | -0.0044*** | -6.425 | -0.0767** | -6.789 | -0.0402*** | -10.473 |
| | (0.0017) | | (0.0015) | | (0.0328) | | (0.0156) | |
| Business | -0.0005*** | -0.595 | -0.0001 | -0.209 | -0.0026 | -0.228 | 0.0011 | 0.292 |
| | (0.0001) | | (0.0001) | | (0.0023) | | (0.0011) | |
| Farming | -0.0019** | -2.039 | -0.0015* | -2.142 | -0.0570*** | -5.048 | -0.0374*** | -9.753 |
| | (0.0009) | | (0.0008) | | (0.0156) | | (0.0076) | |
| Monogamous | -0.0003* | -0.307 | -0.0001 | -0.195 | -0.0039 | -0.345 | -0.0013 | -0.331 |
| | (0.0001) | | (0.0001) | | (0.0031) | | (0.0015) | |
| Polygamous | -0.0006 | -0.641 | -0.0004 | -0.632 | -0.0060 | -0.532 | -0.0034 | -0.887 |
| | (0.0004) | | (0.0004) | | (0.0082) | | (0.0041) | |
| Divorced | 0.0001 | 0.127 | 0.0000 | 0.047 | 0.0049 | 0.429 | 0.0046 | 1.209 |
| | (0.0005) | | (0.0005) | | (0.0104) | | (0.0052) | |
| Separated | 0.0017** | 1.869 | 0.0011 | 1.579 | 0.0158 | 1.402 | 0.0029 | 0.759 |
| | (0.0008) | | (0.0008) | | (0.0173) | | (0.0082) | |
| Never married | 0.0153*** | 16.525 | 0.0126*** | 18.236 | 0.2100*** | 18.599 | 0.1021*** | 26.603 |
| | (0.0022) | | (0.0021) | | (0.0406) | | (0.0207) | |
| No income | 0.0022 | 2.392 | 0.0029 | 4.164 | 0.0369 | 3.267 | 0.0495* | 12.898 |

| | Logistic | | | | Negative binomial | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.0029) | | (0.0027) | | (0.0552) | | (0.0273) | |
| | Suffered illness (dummy) | | Stopped working (dummy) | | Days illness (number) | | Days stopped working (number) | |
| | Coefficients | Percent | Coefficients | Percent | Coefficients | Percent | Coefficients | Percent |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Income (1- 250000 UGX) | -0.0009 | -0.952 | -0.0006 | -0.799 | -0.0112 | -0.995 | -0.0087 | -2.270 |
| | (0.0019) | | (0.0017) | | (0.0359) | | (0.0178) | |
| Income (250,001 – 750,000) | 0.0023* | 2.471 | 0.0015 | 2.115 | 0.0312 | 2.76 | 0.0053 | 1.378 |
| | (0.0012) | | (0.0011) | | (0.0217) | | (0.0111) | |
| Income (> 750,000) | -0.0003 | -0.292 | -0.0001 | -0.118 | -0.0033 | -0.295 | 0.0028 | 0.732 |
| | (0.0005) | | (0.0004) | | (0.0089) | | (0.0045) | |
| Dependency ratio | 0.0001 | 0.140 | -0.0003 | -0.372 | -0.0070 | -0.620 | 0.0014 | 0.375 |
| | (0.0008) | | (0.0007) | | (0.0151) | | (0.0075) | |
| Net usage | 0.0045*** | 4.867 | 0.0017* | 2.479 | 0.0482** | 4.270 | 0.0171* | 4.464 |
| | (0.0010) | | (0.0009) | | (0.0195) | | (0.0094) | |
| Year 2009 | -0.0001*** | -0.079 | -0.0000 | -0.014 | -0.0006* | -0.049 | -0.0002 | -0.056 |
| | (0.0000) | | (0.0000) | | (0.0003) | | (0.0002) | |
| Year 2010 | 0.0001*** | 0.108 | 0.0001*** | 0.103 | 0.0015*** | 0.132 | 0.0004** | 0.093 |
| | (0.0000) | | (0.0000) | | (0.0004) | | (0.0002) | |
| Year 2011 | -0.0000*** | -0.038 | -0.0000 | -0.005 | -0.0002 | -0.020 | -0.0002* | -0.059 |
| | (0.0000) | | (0.0000) | | (0.0002) | | (0.0001) | |
| Year 2013 | 0.0001*** | 0.135 | 0.0001*** | 0.101 | 0.0017*** | 0.147 | 0.0003** | 0.071 |
| | (0.0000) | | (0.0000) | | (0.0003) | | (0.0001) | |
| Observations | 22,469 | | 22,469 | | 22,469 | | 22,469 | |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

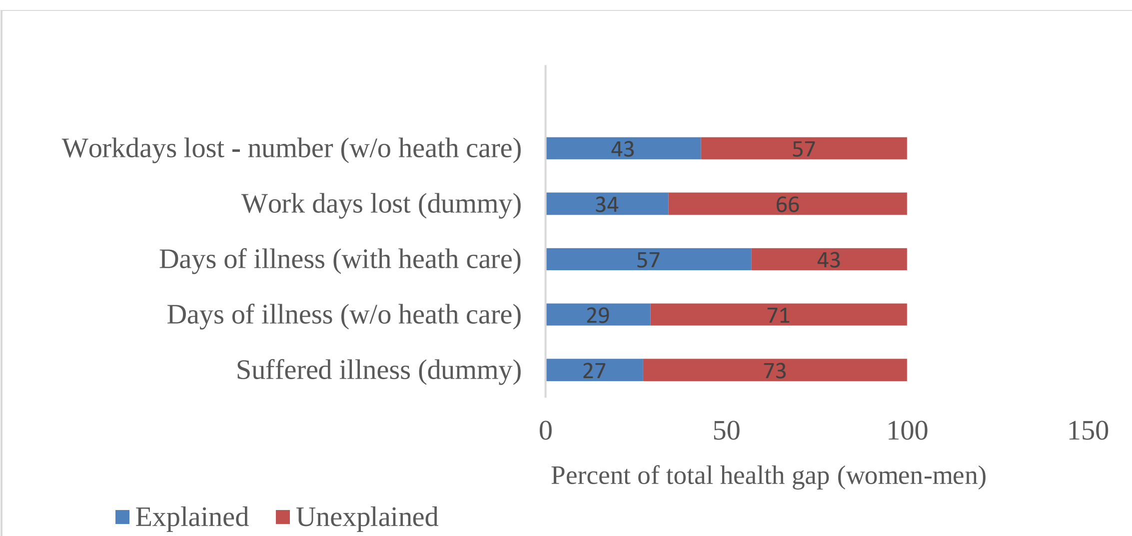


**Figure 3.7**: Summary of explained and unexplained components of total gender health gap

## 3.5 Discussion and conclusion

### Discussion

This study analysed the effects of weather anomalies on days of illness and days of work lost due to illness among men and women groups, established the indirect effect through water collection labour burdens and further established the gender differentials in factors that explain the observed gender gap in health status. This section interprets the findings in relation to the wider literature, and Uganda context. Most studies on the effect of weather or climate or weather anomalies focused on specific diseases, we however took an alternative approach by considering all illnesses captured within the last 30 days prior to the interview. We did so mainly because information was only collected on symptoms rather than particular diseases. Furthermore, most common symptoms among sampled individuals are related to climate sensitive illnesses. A similar study conducted by Lohmann and Lechtenfeld (2015) also used an aggregate illness variable to study the effect of drought induced illness on health expenditures in Vietnam.

Empirical results showed that low rainfall significantly increased the likelihood of illness of the total sample by 7.5 percentage points. These results are consistent with Lohmann and Lechtenfeld (2015) who found out that drought increased the probability of general diseases by about 10 percentage points among individuals. After disaggregating the different diseases into different categories (infections, short-term and long-term non-communicable disease, others), their results were still significant and of higher magnitude especially for infections as well as non-communicable diseases. Even though the magnitude of effect in our study was almost similar to Lohmann and Lechtenfeld (2015) study, they did not find any significance differences by gender (interaction of gender and drought), and furthermore they considered all individuals as opposed to our study which focused on only individuals in the working age. They however revealed that younger people were less sickly than adults, and males also suffered less from a health shock as compared to women. Other studies on effects of droughts and mental health found out that prolonged drought was associated with increased likelihood of psychological distress, especially in the rural areas (Obrien et al., 2014), and drought related worries especially among the working individuals (Stain et al., 2011). However, these studies did not establish the effects of drought on distress on the different gender categories. Apart from the highlighted mental health, Yusa et al. (2015) indicate the importance of drought on other illnesses such as infectious disease, respiratory diseases, injuries and food/water insecurity related illness.

Further results indicate that water collection time fully mediated the relationship between negative rainfall events and illness in women and partially mediated the relationship in men. Full mediation means that occurrence of low rainfall may increase water collection time in women, and in turn, both low rainfall and water collection time burden may directly affect health outcomes. Similarly, water collection time partially mediated the relationship between temperature and illness in both men and women, given that the difference in coefficients was not significant. Part of this result is consistent with other studies on gender, water and health. There may be seasonal patterns with regards to illness and water collection time. However, the coefficients of weather variables remained the same after controlling for seasonal effects. Results showed increased probability of illness in both men and women in the fourth quarter of the year, which is usually drier. The magnitude of effect was greater in men as compared to women. The wetter season - second quarter of the year was negatively correlated with illness in both gender groups. Further results demonstrate that individuals spent significantly less time collecting water during the second quarter compared to the first quarter. This result support our argument that during times of adequate rainfall, individuals spent less time collecting water, thus enough quantities of water translating into better health outcomes.

In most rural areas especially in sub-Saharan countries, including Uganda, division of labour within a household is attributable to gendered power relations. Women are often regarded as predominant providers of household water. Indeed, we found that women allocated more time to water collection activities as compared to men. Therefore, negative effects of dry spell events on water availability, and health are mostly felt by women. Low rainfall may result in water scarcity due to decreased water table thus increasing the distance to the nearest water sources as well as increased waiting time at collection points. Similar studies on water scarcity reported that in Kasalu subcounty of southern part of Uganda, a high proportion of households (85%) spent significantly more time collecting water during drier periods (at least one hour a day) as compared to wet seasons (Mukasa et al., 2021). More time spent at water source and on hilly roads, especially when carrying a heavy container of water has severe health consequences on women and girls. Asaba et al. (2013) study in Uganda revealed that women and children suffered more from health complications associated with water collection such as headaches, chest pains, fatigue and risk of rape and physical assault when conducting water collection activities.

Households may also switch the primary water sources between seasons. For instance, almost 20% of the households in Uganda switched to a water source with high contamination risk from a low risk water source during dry seasons (Pearson et al., 2016). Water inadequacy and poor quality experienced during dry periods have negative effects on health of individuals (Pearson et al., 2016), especially women who are in close contact with contaminated water sources and also have increased water needs during certain periods of their life. Therefore, water technologies that facilitate household water quantity and safe drinking water are recommended. One of the most cost-effective technologies used to address water insecurity in rural areas in the face of changing climate is domestic rain water harvesting, with at least 1 % of Ugandan rural population having accessibility to water harvesting tanks (Staddon et al., 2018). As an improved source, water harvesting reduced significantly the time burdens of water collection in women and men, and reduced the probability of illness in men in this study. We also found that drinking water quality improvement through boiling and filtering was significantly associated with reduced illness in women. These results are consistent with Usman et al. (2019) who found that safely stored water was correlated with decreased diarrhoea in children in rural Ethiopia.

High temperature in the long run and short run significantly increased probability of suffering from illness and absenteeism in both men and women, and further contributed to a significant proportion of the observed gender health gap. The coefficient of the positive temperature deviation was almost similar for both groups, while the coefficient of the temperature prior to the month before interview was higher in men. These results are consistent with Gifford (2019) meta-analysis that reported a high risk of heat related illness in men, after correction for occupation. Other studies that found positive correlation between temperature and specific illnesses without gender dimensions include; (Chowdhury et al., 2018; Sewe et al., 2016; Texier et al., 2013; Tompkins et al., 2019).

One of the major results from the decomposition analysis is that 27 - 54% of the gender gap in health status was explained by the different risk factors, including weather factors, differences in socio-economic and demographic characteristics of men and women. This proportion of gender health inequality is almost similar to (54%) that was reported by Murendo and Murenje (2018) and Zhang et al. (2015) where the explained component of the gender health gap ranged between 31-69% and 66% reported by Madden (2010). However, the proportion attributable to endowments in this study was lower to what was reported by Sia et al. (2014), especially in Lesotho and Tanzania where the gap attributable to gender differences in characteristics was over three quarters.

With regards to contributions of the individual factors to the explained gap, age, years of schooling, marital status (single), income, wealth and occupation were significant and explained a significant proportion of the gender health gap. These results are consistent with Felder (2006) and Madden (2010) for marital status, Zhang et al. (2015) for education and Murendo and Murenje (2018) for wealth. While our findings reveal a reduction in women-men illness gap if men and women income is equalized, Leung et al. (2004) reported that longevity advantage of women in terms of life expectancy will reduce if gender gap in wages or income is narrowed. The study argued that women will spend more time on labour as opposed to health investment, while the converse is true for men (increased health investment) because of increased income for the household (Leung et al., 2004).

Differences in health seeking behaviours indeed explained a significant proportion of the health gap (over half of the total explained component) at the intensive margin of days of illness. From the descriptive statistics, there were no significance differences between men and women who sought consultations, heterogeneity was only observed in the places where they visited for health care services. These results are consistent with Gyasi et al. (2019) and Ssewanyana et al. (2004) who found no significance differences in health care usage among men and women. The former study also reported that adult males sought formal health care than young men and women. However, Stefan (2015) argued that women were more active in health information seeking, from both formal and informal sources, more attentive on healthy life styles and pandemics.

## Conclusions

We examined the effects of weather anomalies on illness in men and women of the working age using the longitudinal LSMS survey from 2009-2014. The study goes beyond establishing total and direct effects of weather variability on illness, and evaluates the extent to which rainfall and temperature affect health, through water scarcity pathway. Furthermore, the study provides new insights on gender differential factors that explain the observed gender health gap at both extensive and intensive margins of illness, including weather events as well as healthcare seeking behaviours.

Generally, both men and women health were negatively affected by weather anomalies at the extensive margins, in terms of likelihood of illness and work days lost due to the illness. Heterogenous insignificant effects were observed at the intensive margin conditional on being sick, where weather anomalies increased the number of days of illness, and reduced the number of sick days in men. The overall effect of weather variables was however significant, positive and of higher magnitude in women than in men. Focusing on mediation analysis, result indicate that water collection time fully mediated the relationship between negative rainfall anomaly and probability of illness in women while a partial mediation process was observed in men. Domestic rain water harvesting played important roles in reducing the time burdens in water collection in both women and women, and improved health in men.

Results further revealed that indeed health care services matter in reduction of the number of illness and number of work day lost, especially in men. Decompositions analysis demonstrated that differences in characteristics accounted for about 27-57% of the gender gap in health status, with over half of the explained gap at the intensive margin explained by differences in health-seeking behaviours. Differences in temperature exposure explained a significant proportion of about 3-5% on the gender gap on the likelihood of illness and work days lost, while differences in age, years of schooling, wealth and never married accounted for significant proportions of the explained gender health gap, at the extensive margin.

Given that women had poorer health than men and were less economically endowed, investment in education, job creation and other income-based investments, water sanitation and hygiene conditions as well as investment in health adaptation such as domestic rainwater harvesting, early warning systems, will aid in reducing the time burdens in water collection and propensity for illness, as well as subsequent days of illness or unproductive days. Strategies that promote women improved access to quality health care, health insurance, time poverty reduction and women empowerment are thus advocated for, so as to reduce the observed gender health gap in Uganda and improve household welfare in terms of food and nutrition choices. This will further help in addressing the sustainable goals 3, 5, 6,13 and 2. Limitations of the study include data deficiency, especially on health behaviours and health adaptation measures. Health outcomes were only available for the last 30 days before the interview, and based on symptoms rather than diseases. Additionally, weather variables were for the enumeration areas as opposed to where the specific individuals spent time.

# Chapter 4: Effect of extreme weather, illness and weather-induced illness on resilience of households

## 4.1 Introduction

Extreme weather events and illness are the most important covariate and idiosyncratic shocks experienced by rural farming households in developing countries. These sources of risks may in isolation or in combination limit economic opportunities and increase economic costs, such as medical expenditures associated with illness, depletion of assets, potentially leading to substantial reductions in consumption and increase in poverty. Vulnerability of rural households in SSA to the negative impacts of both weather and health shocks is mainly due to the absence or limited access to formal insurance markets. Furthermore, households are not well equipped to cope with seasonal variations in consumption as well as health (Devereux et al., 2012), and are not resilient to shocks. Therefore, a better understanding of the effects of weather on health shocks and the resulting effect of both shocks on consumption, including the relevant risk sharing institutions effective in mitigating the negative consequences is crucial for policy makers.

Apart from adaptation, other key components of resilience such as absorptive and transformative capacities that enable households to resist a shock, bounce back and create new systems in times of hardship (Asmamaw et al., 2019), in a timely and efficient way (Oriangi et al., 2019) are gaining recognition. Collectively, these core elements of resilience are crucial in successfully managing emerging risks and important for policy. von Braun and Mirzabaev (2022) highlights that designing of elaborate policies that give optimal response in dealing with the risks requires knowledge on risks probability of occurrence and associated potential outcomes. Since extreme weather events may have adverse effects on human health directly or indirectly through food and water security (Asmamaw et al., 2019), building resilience to climate induced shocks is beneficial to households and have a multiplier effect on a range of welfare outcomes, especially among the poor who are mostly affected by climate shocks. For instance, there is no significant loss of nutrition, health and livelihood of individuals, households or groups that are resilient (von Braun & Thorat, 2014). Furthermore, resilient households are generally more robust to shocks (Ansah et al., 2019) considering that they are able to improve or sustain their standard of living when faced with environmental shocks (Asmamaw et al., 2019) and can deal with future shocks without compromising potential for long-term development (von Braun & Mirzabaev, 2022). In the current world, food resilience against climate change shocks has become an important issue. Therefore, actions geared towards reducing climate induced hazards to food systems, lowering the exposure to food systems risks and reducing food system vulnerabilities are important in increasing food systems resilience (von Braun & Mirzabaev, 2022), in the face of changing environmental conditions.

Given the increase in frequency, intensity and duration of weather or climate related shocks in most parts of world, the effects of climate or weather variability including extreme weather events on consumption among the vulnerable population has been established in the recent past. Gao and Mills (2018) and Amare et al. (2018) report positive effects of increased rainfall on consumption and negative effects of low rainfall on consumption respectively, while Alem and Colmer (2021) find that increased rainfall variability led to significant reductions on consumption and life satisfaction. On the other hand, Letta et al. (2018) and Gao and Mills (2018) document detrimental effects of increased temperature on consumption.

Literature highlights four main channels through which the effects of weather variability on consumption occur. High temperatures and low rainfall may lead to food shortages because of reduced agricultural productivity (Amare et al., 2018; Letta et al., 2018) and total factor productivity (Letta et al., 2018). Moreover, droughts and other climate shocks may affect agricultural prices (Kalkuhl et al., 2016; Letta et al., 2021) and income (Alem & Colmer, 2021; Mendelsohn et al., 2007) which may have direct effect on consumption. Empirical evidence on the negative effect of climate and weather shocks on nutritional quality of foods (Fischer et al., 2019) as well as on diet diversity (Niles et al., 2021) is developing. Taken together, climate related shocks have negative effects on all the four dimensions of the food security (Wheeler & Von Braun, 2013). With regards to health environment, climate variability through the above-mentioned mechanisms may have interlinkages with health outcomes. Literature highlights the direct and indirect effects of climate variability on health, including deaths, injuries, infectious diseases, mental illness, non-communicable diseases (Frumkin, 2020), respiratory diseases, heat stress, food security and nutrition (Watts et al., 2018).

A separate strand of literature focuses on the relationship between health shocks and consumption (Asfaw & von Braun, 2004; Gertler & Gruber, 2002; Hangoma et al., 2018; Islam & Maitra, 2012; Wagstaff, 2007). These studies report mixed results on the effect of health shocks on consumption (food, non-food or both) and other economic outcomes among the rural households. Significant negative effects of health shocks on food consumption are reported by Wagstaff (2007) while Islam and Maitra (2012) find significant negative effects on food expenditures only among households that experienced income loss or big expenditure due to illness. Food expenditure of households experiencing short-term health shocks remained unaffected (Islam & Maitra, 2012). Similarly, Kadiyala et al. (2011) report that adult mortality did not affect food expenditures while Asfaw and von Braun (2004) observe that although effect of illness was insignificant for total food consumption, purchased food was negatively affected by illness. On the other hand, Hangoma et al. (2018) find positive and insignificant effects of injury on food consumption before 2002 and a negative significant effect of injury on food consumption after 2002. In terms of diet quality, adult mortality reduced the number of unique foods consumed, especially among the poor households but the total food groups remained unaffected by illness (Kadiyala et al., 2011).

The effect of health shocks on non-food expenditures is also mixed. For instance, Wagstaff (2007) report increased expenditures on electricity and housing items following a health shock among rural households. Similarly, Islam and Maitra (2012) find a positive and significant effect of health shocks on non-food consumption. On the contrary, Asfaw and von Braun (2004) and Gertler and

Gruber (2002) consistently find negative effects of health shocks on non-food consumption. However, the significant effect in the latter study was only reported on the activities of daily living (ADL) index and not illness symptoms. Insignificant effects of mortality on non-food consumption was reported by Kadiyala et al. (2011).

In summary, some of the studies reviewed fully support the hypothesis of consumption smoothing for households experiencing health shocks while others reject it. Furthermore, there is variation of the effect depending on the type of consumption categories investigated as well as the type of health measures used and the mechanisms explored. For instance, Wagstaff (2007) reports that rural households' sizes are larger, thus their total income is less vulnerable to the health shocks as compared to urban households. Rural households have the ability to undertake relevant labour supply adjustments to compensate for the lost labour of the sick individual. Furthermore, unearned income received from gifts, friends and relatives, remittances and loans as well as other informal arrangements may increase following health shocks and would compensates for shortfalls on earned income (Wagstaff, 2007). This also applies to food consumption where gifts compensate for reductions in purchased food due to illness (Asfaw & von Braun, 2004).

As discussed, the effect of weather variability on consumption and health on consumption have been studied separately. We contribute to the above literature by focusing on both the effect of weather and health shocks on consumption. Very little research has investigated both shocks simultaneously, except Lohmann and Lechtenfeld (2015) who investigated the financial burden (in terms of medical expenditures ) of drought related health outcomes. We also establish the association between food consumption and health shocks. Secondly, the study utilizes a very innovative intra-annual & intra-seasonal high frequency panel collected after every two to three months, to study the short-run connections between health shocks and consumption. We also focus on institutions that households use to insure against health shocks. The research questions addressed in this paper include; (1). What is the effect of extreme weather, illness and weather-induced illness on household total consumption, food and non-food consumption? What are the possible mechanisms? What is the association between food consumption and health? (2) Which coping strategies are effective in insuring household consumption against illness? The hypothesis are as follows, (1) Weather-related illness will reduce consumption on food and non-food items. (2) The negative effect of weather-related illness on consumption will be mediated by changes in medical expenditures, labour supply and wages (3) An increase in food consumption and diet diversity will lead to better health (4) Insurance mechanisms (group networks, loans, assets and free medical services) will mitigate the adverse effects of weather and illness on consumption.

The rest of chapter four is structured as follows. Section 4.2 presents theoretical and conceptual frameworks. Section 4.3 outlines materials and methods, including data sources, data variables, descriptive statistics and empirical framework. The empirical results are detailed in section 4.4 while section 4.5 presents relevant discussions and conclusions.

## 4.2 Theoretical and conceptual framework

**Theoretical framework**

The theory guiding this study is the theory of full insurance, which states that households consumption growth rate will be independent of shocks, especially idiosyncratic risks such as illness affecting household resources and income (Asfaw & Braun, 2004; Cochrane, 1991; Gertler & Gruber, 2002), if households group themselves to perfectly share and manage risks (Townsend, 1995). This implies that risk averse households are protected from these risks and household consumption will only depend with community average consumption given that preferences do not change frequently (Islam & Maitra, 2012). Most rural households especially in low- and middle-income countries use different formal and informal risk sharing mechanisms such as informal networks, borrowing, savings, markets and technologies either jointly or singly for consumption insurance when faced with a health burden such as major illness or other shocks that have economic consequences on the households.

**Conceptual Framework**

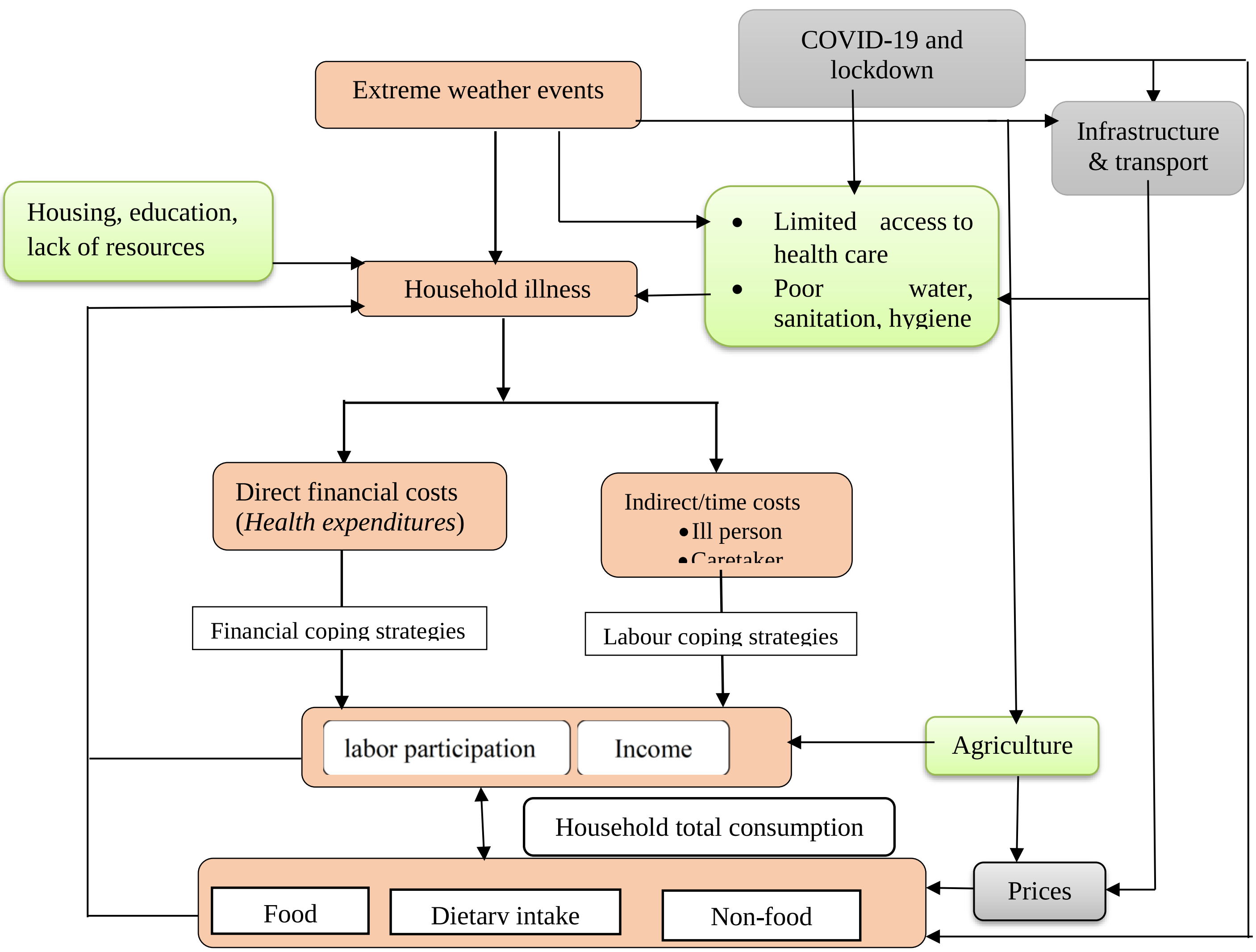

**Figure 4.1**: Conceptual framework – linkages on weather shocks, illness and consumption

The conceptual framework in Figure 4.1 summarizes the interlinkages between extreme weather events and illness and their effects on consumption, taking into consideration the potential pathways. Furthermore, the framework highlights coping strategies that households use to minimize both the financial and time costs associated with illness which are likely to affect household income and consumption. It is anticipated that illness will only affect consumption negatively if there is a considerable cost of illness, and under imperfect insurance conditions (Gertler & Gruber, 2002).

Direct costs of illness include both medical and non-medical expenses incurred while seeking treatment while indirect costs include loss of productive labour days in economic activities. In agricultural household's illness experienced during critical farm activities such as planting may have adverse consequences on crop output because resources planned for purchasing inputs may be reallocated to cover health expenses. In addition, illness may limit farmers ability to innovate, acquire extension information and implement changes on the farm (Asenso-Okyere et al., 2011).

More importantly, less labour may be supplied to the respective farm activities and decrease in labour productivity experienced. Illness may also hinder individual participation in wage labour markets either in agricultural or others non-farm sectors leading to reduced household earnings. Therefore, in events of adverse health outcomes and absence of social protection measures, risk sharing institutions and labour related coping strategies; catastrophic health expenditures, productivity and income losses may eventually affect household consumption.

Even though some coping strategies are effective in smoothing consumption in the short term, they might deplete household assets and push affected households into poverty (Alam & Mahal, 2014), thus unsustainable in the long-run. While health is an individual specific occurrence, this study analyses the abovementioned interlinkages at household level because direct and indirect costs of illness in developing countries are mostly incurred by both the sick person and the caregiver, and decisions regarding treatment, coping and consumption are established partly through negotiations (Russell, 2004). Furthermore, most illness costs, food and non-food expenditures are financed from households' budgets, and adjustment strategies practiced by other household members.

Since the study was conducted during COVID-19 period and in between two major lockdowns (as shown in appendix Figure 7.3, we highlight all possible linkages between COVID-19 and related lockdowns with health and consumption. The main pathways through which COVID-19 effects are likely to affect consumption is through distortions of supply value chains due to transport limitations, income and closure of institutions and non-essential services. However, we only focus on the linkages that occur through weather variability mainly because our sampled respondents are from rural areas and the agricultural sector where most rural households derive their livelihoods was labelled as "*a fully functioning sector*" in both lockdowns. Additionally, we control for survey wave specific characteristics or shocks, that changes every wave and common to all households by inclusion of wave fixed effects. According to FSIN and Global Network Against Food Crises

(2021 ) urban food security situation in Uganda was more affected by COVID-19 restrictive measures as compared to rural areas. Thus, the grey labelled variables are beyond the scope of this paper. However, we provide descriptive statistics on some of the variables affected by COVID-19. Our study contributes to previous frameworks by focusing on weather-related health components using an innovative panel dataset collected over multiple rounds in different seasons of the year.

## 4.3 Materials and methods

### 4.3.1 Data sources

**Household High frequency panel survey (HFPS)**

A rich short-term panel data collected as part of the ZEF project "Analysis and Implementation of Measures to Reduce Price Volatility in National and International Markets for Improved Food Security in Developing Countries" are used in the empirical analysis. The datasets were collected in collaboration with College of Agriculture and Environmental Sciences, Makerere university. The researchers collaborated with community leaders maintaining a hierarchal entry strategy to (re)visit sampled households in the selected districts. First, reporting to the Resident District Commissioner (RDC) and then to community leaders of the selected villages. This was crucial to minimize attrition and enhance rapport between the researcher and the respondents. The research assistants participating in the surveys had a background in agriculture related concepts and proficient in local dialects.

Given that the surveys were conducted during the COVID-19 period, all mandatory COVID-19 Standard operating procedures (SOPs) were observed by research assistants. Before the actual survey, training was conducted on both the questionnaire and COVID-19 SOPs, where researchers were informed of measures to be observed. Furthermore, the researchers were equipped with necessary materials including face masks of both researcher and the respondent as well as hand sanitizers to comply with the Ministry of Health precautionary measures. The survey activities were carried out between June 2020 and August 2021 with a total of six waves collected after every 2-3 months in June/July, September, December, March, May and August of 2020 and 2021 as shown in Table 4.1. The first round (wave) of survey was conducted just after the partial lifting up of the first lockdown while the last wave was conducted after the second COVID lockdown. The timelines of different survey waves and trend of COVID-19 daily new cases are shown in Figure 7.3 of the appendix. During the survey period, some districts in the Karamoja were experiencing insecurity issues due to cattle raids, and its reported that COVID-19 restrictions exacerbated the raids because of the difficult economic hardship amidst crop failure leading to increased violence and loss of lives (REACH, 2021).

The questionnaires were administered through face to face interviews on the sampled respondents using Computer-Assisted Personal Interviewing (CAPI) tool. Comprehensive information on key elements such as assets and livestock ownership, shocks, health indicators, income, family labour allocation, food and nonfood consumption, household demographics, social participation, maternal and children diets and food security indicators were collected for every wave. Data on crops planted, input use, harvest and utilization of harvest was also collected for each wave, but only on elements relevant for the particular season in which data was collected. Other time invariant datasets collected either in the first wave or the last wave include water, sanitation and hygiene indicators, housing conditions, distances, savings, access to information, networks, time and risk preference games, and COVID-19 related questions. The questionnaire administered was slightly modified from the Nutrition Innovation Laboratory Africa (NILA) questionnaire and questions related to anthropometric measurements dropped because of the requirement of social distancing.

The sampling strategy was also a slight modification from NILA multi-stage sampling strategy. The study was conducted in eight districts located in three regions of Uganda (North, East and West). These districts were purposively selected based on occurrence of either climate or price shocks in the recent past. Four of these districts namely Kole, Lira, Kamwenge and Kisoro were covered by NILA panel survey conducted in 2012, 2014 and 2016 while four were new districts (Kotido, Moroto, Sironko and Bududa). For the latter category, a sampling frame of all sub-counties, parishes and villages in each of the four new districts was obtained from UBOS, and four sub-counties were randomly selected to match the same number of sub-counties in each district selected under the NILA strategy.

All parishes in the selected sub-counties qualified to participate in the study while only 25 percent of the villages in each Parish were randomly selected, excluding villages within town councils. A sampling frame of households in the selected villages (25%) was collected by researchers at Makerere university in collaboration with community leaders and a probability proportionate to size sampling strategy used to select 80 households per district leading to a total of 320 households for the new districts. With regards to NILA districts, a list of households from the last wave (2016/2017) was used as a sampling frame, where 80 households were randomly selected from each district. In total, a sample of 640 households were selected from 8 districts, as shown in Figure 4.2 and considered for data collection. Excluding duplicates, unique household’s data was collected on 638 households in the baseline survey. For the rest of the waves, the attrition rates were relatedly low, a maximum of 2% from first to last wave. However, in our analysis we only consider a balanced dataset of 621 households.

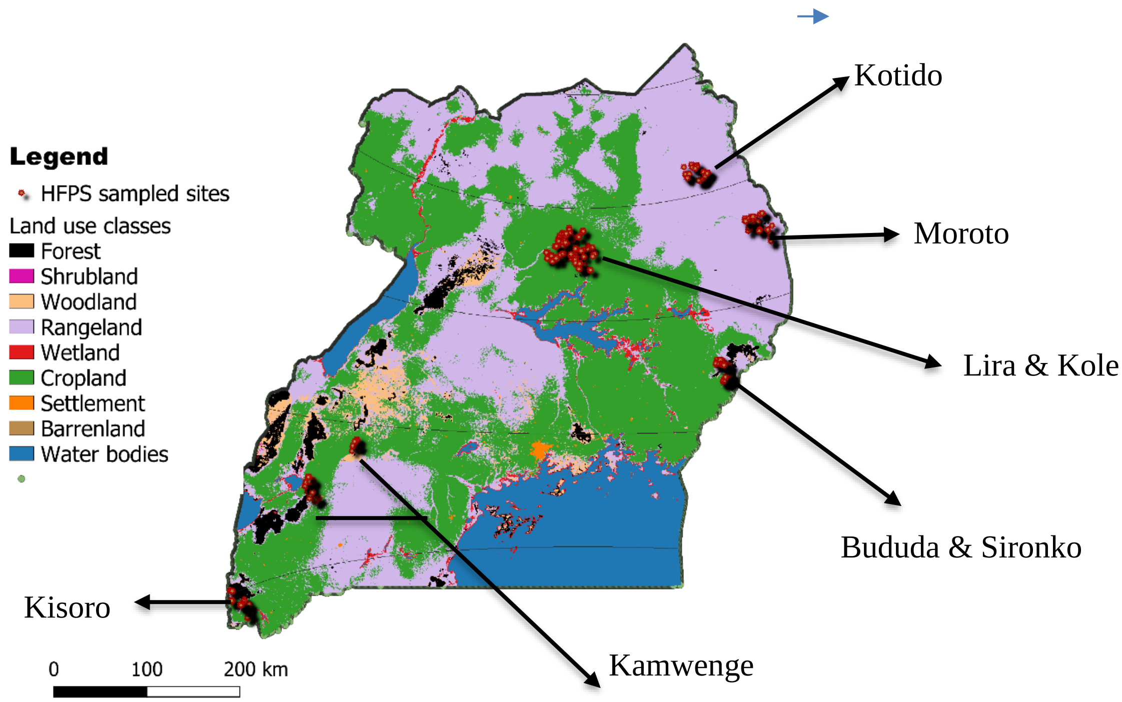


**Figure 4.2**: A map of Uganda showing HFPS sampled sites and the different land use types[26]

### Timing of surveys and sampled households

Due to seasonal fluctuations of food availability and income among rural households in developing countries, seasonality was very important in the timing of the surveys. Seasonality also plays a key role in spread of diseases. Wet season that occurs from the onset of rains until before harvest is the most important and difficult time and has been documented to be both a sick season and a hungry season in most tropical countries (Chambers, 1982, 2014). During this time, physical energy is needed for different farm activities, yet there is shortage of food, prices are high and households incapacitated with high prevalence of sickness such as diarrhoea, malaria, skin diseases. Furthermore, due to high demand of farm labour, women have less time for other domestic tasks such as cooking, child care and hygiene. It's also a time when health services in rural areas are least effective due to damaged roads because of rains despite the high demand due to increased sickness, therefore mortality is high. During this period, the poor are at their poorest and many people are vulnerable of becoming poor (Chambers, 1982).

COVID-19 restrictions also played a key role in determining when the surveys were conducted, since it was impossible to conduct survey activities when domestic transport was prohibited. For instance, the first round of survey planned for April during lean season was only conducted in June 2020 (harvest season) and second wave also conducted during harvest/post-harvest season.

[26] Land use types are based on 2018 MODIS data

Sampled households rely mostly on rainfed agriculture and therefore agricultural production especially for annual crops depend on seasonal cycles, with weather extremes playing a crucial role in production. Most of the surveyed districts experience bimodal type of rains except Moroto and Kotido which experience unimodal rains. Uganda has a diversified farming system and rich agroecological diversity which varies across regions. Livestock-based system are common in semi-arid areas while households in humid and temperate regions practice a mixed type of crop-livestock systems. Land use type for most of livestock keepers is rangeland which dominates most of the areas that fall under the "cattle corridor" of Uganda – stretching from north east to south west as shown in Figure 4.2. Moroto and Kotido districts are some of the districts located in this zone. Other sampled sites are located on crop lands, with part of households in the west and east regions located or neighbouring forested land.

Due to diversity and regional differences in food systems and seasons, the harvest season also varies across sampled districts. There is continuous harvesting for perennials throughout the year. Most of the first season harvesting for annual crops within the survey period was done between June to August while second season harvesting varied across districts ranging from October to February. The main harvest season for unimodal rainfall type in Karamoja occurred in Oct, Nov and Dec. However, green consumption and harvest of some crops usually starts as early as July. Lira and Kole have an extended harvest period especially for cassavas and sweet potatoes until February. Considering selected major food groups in different regions (beans, maize, millet, cassava and sweet potato) , Food and Agriculture Organization of the United Nations (2021a) defined the period between March -May 2020 and October -December 2020 as lean seasons for areas with two seasons while march-July as a lean season for Karamoja, with the latter being consistent with FEWSNET calendar for a typical year. Using this criterion, wave 4 conducted in May with the 2 months recall period in march April falls under the lean season for all surveyed areas. Other survey rounds conducted in June, December and March can also be categorized as lean seasons for specific districts.

**Table 4.1:** Dates of high frequency survey rounds

| Survey | Survey start dates | Number of households |
|---|---|---|
| Round 1 (Baseline) | 22 June 2020 | 638 |
| Round 2 | 31 August 2020 | 637 |
| Round 3 | 14 December 2020 | 633 |
| Round 4 | 01 March 2021 | 631 |
| Round 5 | 10 May 2021 | 626 |
| Round 6 | 7$^{th}$ August 2021 | 623 |

**Weather data**

We use publicly available rainfall and temperature datasets. Using the georeferenced household data in the HFPS, we match each household with temperature and rainfall data. Rainfall datasets comprise the CHIRPS data version 2 from 1990 to august 2021 while temperature was retrieved from MODIS for the time period 2000 to 2021. Figure 4.3 shows the average monthly rainfall patterns and annual average rainfall for the sampled districts. On average, the survey start year (2020) was the wettest year on record for the sampled areas. However, there existed regional variations where higher rainfall was recorded mostly in Sironko and Bududa as shown in Figure 4.3b. Moroto and Kotido districts also experienced higher rainfall in 2020 as compared to other years while in Lira and Kole, the rainfall amounts were almost the same as 2019. Average rainfall for southwestern districts (Kisoro and Kamwenge) in 2020 were relatively low compared to 2018 but higher than 2019.

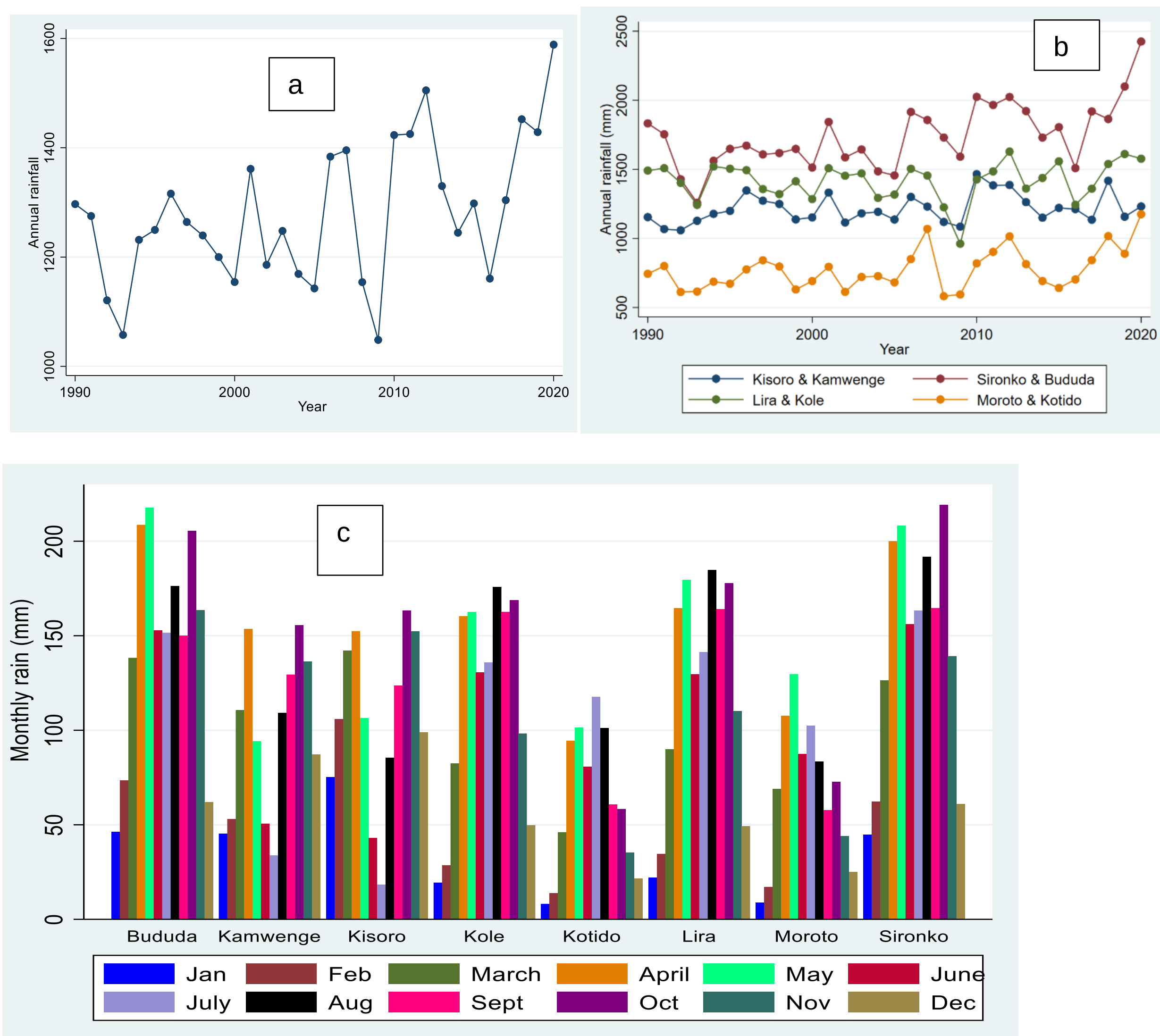


**Figure 4.3**: CHIRPS Rainfall data for all sampled households (A), across districts (B and C)
*NB: Both annual and monthly mean range from (1990-2020)*

For monthly rainfall, Kotido and Moroto receives a unimodal type of rainfall, with relatively good rains between April to October. January, February and December are the driest months in all districts, except in Kamwenge and Kisoro where December rainfall is relatively higher as compared to June and July as shown in Figure 4.3c. Kole, Lira, Sironko and Bududa also experienced a shortfall of rain in June/July which is mostly a harvest season. All of the above-mentioned districts experienced high rainfall between March -May for the first season and August to Oct/Nov for the second season. As earlier mentioned, some of the districts experienced a wetter second season, with more rainfall in months that were historically dry.

### 4.3.2 Data Variables

The primary outcome variable of the study is the value of total consumption per capita, comprising of mean values of all food consumed by the household as well as non-food expenditures (excluding medical expenditures) divided by the household size. Food consumption consists of all foods and beverages consumed out of purchases both at home and away from home, food consumed from own produce as well as gifts in the last seven days. Different categories of non-food consumption include non-durable goods and frequently purchased services such as rent of rented house, fuel, power, soaps, toothpaste, matches, cosmetics, handbags, transport and communication expenditures and other services such as sports, barber and beauty, house assistants and laundry. Semi-durable and durable goods consist of clothing and footwear, furniture, furnishings, household appliances and equipment, utensils, expenditures on education and household functions. We also consider non-food expenditures from non-consumption items such as taxes, user fees and charges, interest on loans, remittances and other social functions such as funerals. Non-food expenditures were collected over two months recall period. Given the different recall period for food and non-food items, the value of food items in the last 7 days is converted to two months period in order to construct a total consumption variable. Similar scaling approaches to derive total food consumption given different recall periods have been used previously (Alem & Colmer, 2021; Islam & Maitra, 2012) .

The household dietary diversity indicator is computed from household food consumption expenditure section where different food elements consumed in the previous 7 days are grouped into 12 food groups (Swindale & Bilinsky, 2006), and aggregated at household to compute the total count of food groups. These food groups include; cereals (1), starchy foods roots and tubers (2), legumes and pulses (3), vegetables (4), fruits (5), meat and offal (6), fish and fish products (7), eggs (8), milk and milk products (9), oils and fats (10), sugar and honey (11), and others/beverages/miscellaneous (12).

The main explanatory variables include short-term health indicators and weather shocks, matching the recall period for consumption. Three health shocks are constructed from the health module where data on illness and injury in the last two months were collected on all household members. The first health measure is a continuous variable (total number of sick days aggregated at household level), the second one is a dummy variable whether any household member was sick for more than 30 days and the last variable is also a dummy variable whether any household member was hospitalized at least for one night due to illness or injury. We believe that these three measures would likely affect financial expenditures on health care as well as income earning activities of either the sick or the caregiver, in the absence of health insurance, free health services as well as necessary adjustments to the lost labour.

Our weather shock measures are constructed from rainfall and temperature data (z scores of weather variables, based on two months rolling averages of weather. That is, weather in the specific two months matching the recall period to the average weather for the same months for historical years under consideration. We start by summing up the monthly rainfall amounts for each two months corresponding to the recall period for each survey wave. In addition, we construct a historical rainfall average for each of the two months from 1990 for each household and proceed to calculate rainfall anomaly based on the difference between rainfall amounts for a particular wave time period t and their corresponding long run averages divided by the long-term standard deviations. For temperature, average temperature for the two months is used as opposed to totals as in the case of rainfall. We use standardized statistical z scores. Similar procedure of constructing weather anomaly has been used previously (Amare et al., 2018; Letta et al., 2018) Michler et al 2018).

In order to derive our shock measures (severe to extreme events), we construct dummy variables bases on the z values of rainfall and temperature. We are particularly interested in extreme rainfall events defined by rainfall z values of greater than 1.5, therefore a dummy variable with 1 indicates that rainfall level that is 1.5 standard deviation or more above the long-run mean. World Meteorological Organization (2012) defines SPI values of 1.5 to 1.99 as very wet and beyond 2 as extreme wet. With regards to temperature, we use z scores cut off of +1 for extreme hot conditions. We focus on extreme rainfall because diverse health outcomes have been associated with flooding, especially infectious diseases outbreaks in developing countries (Few et al., 2004). These disease outcomes include diarrhoeal diseases or diseases transmitted through faecal-oral route such as cholera or hepatis A and E (Few et al., 2004), other gastrointestinal disease and respiratory infections (Guo et al., 2020). These health outcomes are transmitted when humans drink water of food contaminated with the infectious agents, or exposed to contaminated water (schistosomiasis). Transmission of other vector-borne diseases such as malaria are associated with rainfall and both diarrhoea and malaria have seasonal peaks. Flooding can also have direct effects such as injuries and mortalities and indirectly by destroying health infrastructure and limiting access to essential drugs or vaccinations thus exacerbating other health risks as well as mental health (Few et al., 2004). Similarly, temperature changes may have adverse effect on health by enhancing suitability and abundance of vectors and pathogens responsible for waterborne and vector borne diseases (Haines et al., 2006; Watts et al., 2018).

As much as low rainfall or droughts may have detrimental effect on health, we only incorporate this variable in the initial analysis but not in subsequent analysis. Extreme low rainfall is defined as rainfall below -2 SD.

### 4.3.3 Descriptive statistics

Table 4.2 presents the means of household characteristics, weather shocks, medical expenditures, labour participation, consumption and risk sharing institutions. Household size was about 7 members per household per wave, on average. A high proportion of households experienced floods or extreme wetness in the second and third wave as compared to other waves. Based on objective weather measures, 25% of households experienced extreme wetness in the $2^{nd}$ wave while only 7% subjectively indicated to have experienced floods. These results are consistent with Food and Agriculture Organization of the United Nations (2020a) which reported that most areas in Uganda experienced abundant rainfall in September, October and November 2020 with floods and landslides occurring in some districts located in the north, east and southwest parts of Uganda. Furthermore, frequency of flooding has increased in most parts of the country, including arid areas which experiences flash floods due to increased rainfall intensity (World Bank Group, 2020).

This extreme rainfall led to not only loss of lives but also crop losses and damage to the infrastructure disrupting trade. It is estimated that due to flooding events, prices increased in September by about 15-20 percent (Food and Agriculture Organization of the United Nations, 2020a).

For Karamoja districts, continued seasonal rainfall until October reduced cropped area and led to an increase in postharvest losses and below-average production estimated at 10-20% (Food and Agriculture Organization of the United Nations, 2020a). However, increased rainfall had positive effects on pasture resulting into above-average production of milk and meat (Food and Agriculture Organization of the United Nations, 2020a).

More households in wave 6 (23.8%) experienced extreme temperature (temperature greater than 1 SD from the long-term mean of the specified months). The low proportion of the objective temperature measure compared to subjective measure on droughts /heatwaves in wave 6 could be due to the fact that the subjective measure combined both the drought measure as well as the heat measure. Nevertheless, the higher values of these two measures were consistently in wave 6. Furthermore, it's the only wave where temperature z scores were averagely positive and rainfall z scores were the lowest.

The 2 months recall period for wave six conducted early august was June and July. These months fall in the relatively dry season where harvesting of most crops is done for the first season harvest crop for areas that receive bimodal type of rain. For Karamoja, it's a period of continued rainy season and according to Famine Early Warning System Network (2021), rainfall amounts in June and July 2021 were below average, a deficit of 50-100mm. Furthermore, these months fall within the coolest season in the country which range between June to September and according to previous climate projections, warming is expected in these months where temperatures are projected to increase by at least 1.5 °C to up to 5.4°C by the end of the century (World Bank Group, nd).

**Table 4.2**; Summary statistics

| Variables | Wave 1 (N=621) | Wave 2 (N=621) | Wave 3 (N=621) | Wave 4 (N=621) | Wave 5 (N=621) | Wave 6 (N=621) | All waves (N =3726)) |
|---|---|---|---|---|---|---|---|
| Month of survey | **June-July** | **Aug-Sept** | **December** | **March** | **May** | **August** | **June to august** |
| Year of survey | **2020** | **2020** | **2020** | **2021** | **2021** | **2021** | **2020/21** |
| Household size | 6.626 | 6.858 | 7.016 | 6.824 | 6.729 | 6.594 | 6.775 |
| | (2.404) | (2.535) | (2.615) | (2.627) | (2.618) | (2.629) | (2.575) |
| Droughts/heat waves | 0.043 | 0.019 | 0.032 | 0.024 | 0.006 | 0.502 | 0.105 |
| (1 =Yes)- subjective | (0.204) | (0.137) | (0.176) | (0.153) | (0.080) | (0.500) | (0.306) |
| Floods (1 =Yes) - subjective | 0.006 | 0.069 | 0.040 | 0.009 | 0.009 | 0.002 | 0.023 |
| | (0.080) | (0.254) | (0.196) | (0.098) | (0.098) | (0.040) | (0.149) |
| Rainfall Z scores (2 months) | -0.153 | 0.741 | 0.969 | 0.358 | -0.319 | -0.652 | 0.157 |
| | (0.715) | (1.915) | (1.560) | (1.389) | (1.336) | (0.845) | (1.474) |
| Extreme rainfall | 0 | 0.253 | 0.240 | 0.127 | 0.225 | 0 | 0.141 |
| (1 =Yes) - objective | | (0.435) | (0.427) | (0.333) | (0.418) | | (0.348) |
| Temperature Z scores (2 months) | -0.226 | -0.394 | -0.398 | -0.343 | -0.145 | 0.129 | -0.229 |
| | (0.795) | (0.838) | (0.816) | (0.997) | (1.049) | (1.095) | (0.957) |
| Extreme temperature (1 =Yes) - objective | 0.016 | 0.008 | 0.034 | 0.122 | 0.182 | 0.238 | 0.100 |
| | (0.126) | (0.089) | (0.181) | (0.328) | (0.386) | (0.426) | (0.300) |
| HHs member sick (1 =Yes) | 0.712 | 0.816 | 0.763 | 0.717 | 0.683 | 0.617 | 0.718 |
| | (0.453) | (0.387) | (0.425) | (0.451) | (0.466) | (0.487) | (0.450) |
| HHs number of sick days | 15.491 | 16.101 | 15.099 | 12.666 | 10.366 | 9.174 | 13.149 |
| | (22.461) | (19.827) | (18.284) | (17.840) | (14.309) | (12.583) | (18.039) |
| HH member sick more than 30 days (1 =Yes) | 0.098 | 0.113 | 0.114 | 0.092 | 0.063 | 0.047 | 0.088 |
| | (0.298) | (0.317) | (0.318) | (0.289) | (0.243) | (0.211) | (0.283) |
| Number of work days lost due to illness | 8.699 | 8.937 | 7.902 | 6.787 | 6.229 | 5.452 | 7.334 |
| | (13.791) | (11.5030 | (10.933) | (11.629) | (10.179) | (8.707) | (11.295) |
| Household member sick & admitted (1 =Yes) | 0.130 | 0.198 | 0.193 | 0.148 | 0.111 | 0.103 | 0.147 |
| | (0.337) | (0.399) | (0.395) | (0.355) | (0.315) | (0.304) | (0.354) |
| Total health expenditures (UGX) | 49,082 | 51,278 | 46,429 | 39,469 | 34,162 | 39,575 | 43, 332 |
| | (171,233) | (122,826) | (102,827) | (104,598) | (102,683) | (124,968) | (123,947) |
| Paid labour force participation (1 =Yes) | 0.614 | 0.634 | 0.520 | 0.554 | 0.649 | 0.551 | 0.587 |
| | (0.487) | (0.482) | (0.499) | (0.497) | (0.478) | (0.498) | (0.492) |
| Wage income (UGX) | 208,565 | 248,079 | 224,714 | 265,132 | 252, 203 | 206,467 | 234,193 |
| | (554,384) | (615,989) | (692,471) | (616,450) | (582,996) | (498,814) | (596,537) |
| HHs total family labour (pers days) | 33.659 | 17.429 | 40.190 | 20.507 | 57.005 | 19.318 | 31.352 |
| | (53.659) | (26.991) | (67.356) | (29.709) | (70.703) | (40.334) | (52.962) |
| Food consumption per capita (UGX) – 2month | 88,022 | 82,657 | 76,196 | 78,009 | 71,740 | 75,736 | 78,727 |
| | (64,991) | (58,995) | (51,546) | (59,427) | (56,722) | (88,284) | (64,598) |

| | Wave 1 (N=621) | Wave 2 (N=621) | Wave 3 (N=621) | Wave 4 (N=621) | Wave 5 (N=621) | Wave 6 (N=621) | All waves (N =3726)) |
|---|---|---|---|---|---|---|---|
| Household diet diversity | 7.142 | 7.375 | 7.192 | 7.320 | 6.936 | 6.886 | 7.142 |
| | (1.979) | (2.073) | (2.088) | (2.261) | (2.148) | (2.179) | (2.129) |
| Non-food consumption- pecapita | 19,926 | 34,819 | 37,720 | 42,781 | 43, 961 | 29, 525 | 34,789 |
| | (25,960) | (85,277) | (62,249) | 105,380 | (86,707) | (57,940) | (75,455) |
| Total consumption value (food & nonfood) | 107, 948 | 117,476 | 113, 917 | 120,790 | 115, 702 | 105,262 | 113,516 |
| | 77,228 | (119,606) | (89, 640) | (133,808) | (111, 632) | (116,032) | (109,705) |
| Health or wellbeing group (1 =Yes) | 0.069 | 0.061 | 0.167 | 0.208 | 0.227 | 0.262 | 0.166 |
| | (0.254) | (0.239) | (0.374) | (0.406) | (0.419) | (0.440) | (0.372) |
| Financial group | 0.434 | 0.586 | 0.543 | 0.634 | 0.604 | 0.581 | 0.564 |
| (1 = Yes) | (0.496) | (0.493) | (0.498) | (0.482) | (0.489) | (0.494) | (0.496) |
| Loan income (1 =Yes) | 0.024 | 0.040 | 0.043 | 0.039 | 0.035 | 0.034 | 0.036 |
| | (0.154) | (0.197) | (0.204) | (0.193) | (0.185) | (0.181) | (0.186) |
| Remittances | 0.069 | 0.034 | 0.045 | 0.056 | 0.066 | 0.055 | 0.054 |
| | (0.254) | (0.181) | (0.208) | (0.231) | (0.249) | (0.228) | (0.226) |
| Free medical services | 0.242 | 0.293 | 0.206 | 0.211 | 0.208 | 0.153 | 0.219 |
| | (0.428) | (0.456) | (0.405) | (0.408) | (0.406) | (0.360) | (0.413) |
| Asset value | 5,446,490 | 5,381,064 | 5,436,732 | 498,7221 | 5,025,970 | 5,724,159 | 5,333,606 |
| | (11,081,973) | (11,308,067) | 10,484,310 | 8,665,275 | 9,010,774 | 11,223,223 | 10,347,101 |
| Asset ownership (1= Female) | 0.428 | 0.457 | 0.424 | 0.443 | 0.425 | 0.380 | 0.426 |
| | (0.495) | (0.498) | (0.495) | (0.497) | (0.495) | (0.486) | (0.495) |
| Livestock value | 1,709,576 | 1,710,812 | 1,911,948 | 1,739,105 | 1,613,469 | 1,624,909 | 1,718,303 |
| | (3,367,794) | 3,026,407 | (4,553,025) | (2,834,471) | (2,356,208) | (2,473,873) | (3,186,252) |

*NB; Other variables to be included in the model include risk preferences, household characteristics and distance measures. Some of these variables were collected in only one wave.*

For the high prevalence of subjective droughts in wave 6, it could also be possible that farmers define droughts based on the harvest and since wave 6 was a harvest season, farmers are likely to report any drought that occurred within the first season of 2021. Indeed, food consumption in wave 6 was lower as compared to wave 1 and wave 2 conducted within almost the same time during harvest/postharvest season of first season. Sickness was a common phenomenon, with at least 71% of the households reporting at least one-member sick in the last two months. This figure is lower that the prevalence of sickness in 2009-2014 based on the LSMS data, where 80% of households had at least one-member sick, implying a reduction in sickness. However, its important to note that the recall period for sickness in LSMS data was 1 month as opposed to 2 weeks. More households in wave 2 were sicker while households in wave 6 were less sick both in terms of the proportion of households as well as the total number of illness days and number of work days lost due to illness. Similarly, a higher proportion of households in wave 2 and 3 reported incidences of at least one member hospitalized due to illness. There is a likelihood that extreme rainfall partly contributed to the high incidence of sickness in households given a high proportion of households experiencing extreme rainfall and sickness were in waves 2 and 3. Moreover, a low prevalent of sickness and less flood events were recorded in wave 6.

We expected the resurgence of COVID- 19 that occurred in the country since May 2021 to have adverse health effect on most households. However, none of the households indicated to have suffered from COVID/19. In fact, the proportion of households' sick in the last wave was lower than in other waves. After disaggregating the selected symptoms, by wave number, we still find a lower disease prevalence in wave 6. Unfortunately, the symptoms for the common infectious diseases previously experienced in the country such as malaria and others which are likely to be influenced by weather variability are the same as some of COVID-19 symptoms thus difficult to discern if households actually suffered from COVID-19 or not. Figure 4.4 shows the proportion of households with at least one-member suffering from selected illness. Malaria or fever was the most common illness reported by at least 40% of the households in each wave, followed by coughing, severe headache, flu and diarrhoea.

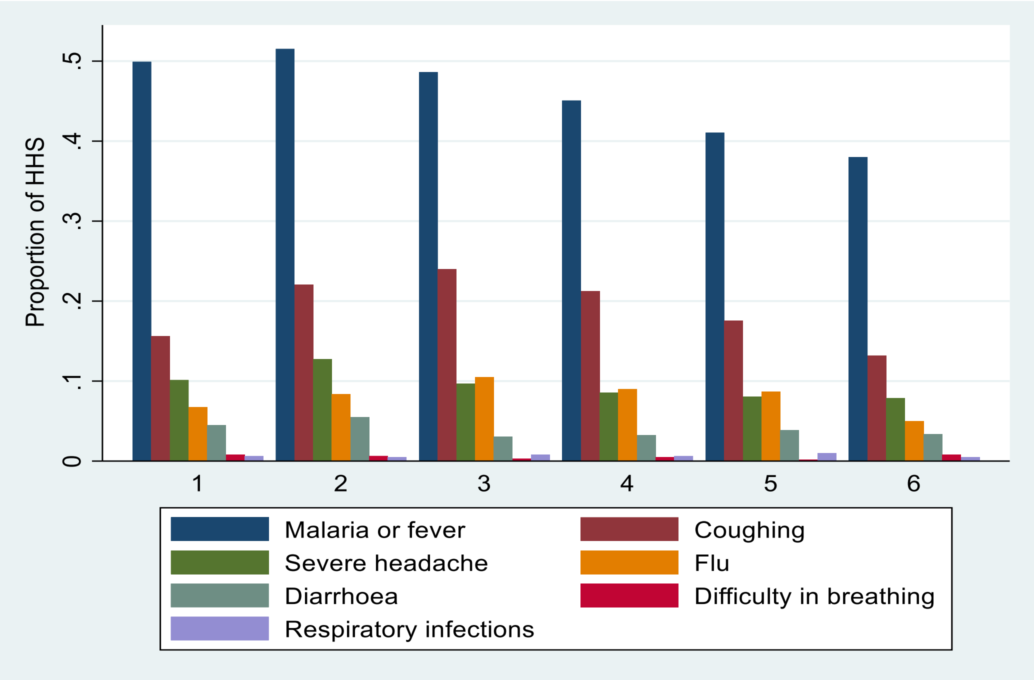

**Figure 4.4**: proportion of households suffering from different illness

We also asked households if COVID-19 lockdowns implemented in March 2020 and June 2021 limited their access to medical services. These questions were as follows; if any member of the household fell sick during the lockdown and was unable to access health care services, if any member delayed, skipped or was unable to complete any scheduled health care visits during lockdown and if children been unable to complete vaccination / immunization during the national lockdown period and if any household member was unable to obtain prescription medications. Results in Figure 7.4 of the appendix shows that only 7% of the households were affected in either lockdown. A higher proportion of households 9% were affected in the 1st lockdown as compared to the 2nd lockdown (5%). Majority of these households were sick and unable to access health care and some delayed or were unable to complete any scheduled health visits due to lockdown. Around 2% of the households were unable to obtain prescription medications and less than 2% were unable to complete children vaccination / immunization due to the national lockdown. Most of the households affected in the baseline indicated that transport means were unavailable, and for those who accessed, they could not afford transport as shown in Figure 7.5 of the appendix. During the baseline study, most sampled districts had not registered any COVID-19 case except Lira district. As indicated in Figure 7.4, 18% of the households in Lira district indicated they were affected by the first lockdown. In the second lockdown, both Lira and Kisoro districts were mostly affected. Kisoro is a border country, bordering Rwanda and democratic republic of Congo.

Health expenditures were highest in wave 2 followed by waves 1 and 3. Approximately 22 % of the households received free medical services. Other common sources of financing health care include household's savings (27.2%), agricultural sales (14%), borrowing from friends and relatives (7%), assistance from friends and relatives (6.5%), livestock sales (7.3%) as shown in Figure 4.7. With regards to labour force participation, over half of the households participated in wage related activities across all waves. However, participation was higher in the fifth and second wave with 65% and 63% of households participating in any wage labour markets respectively. Similarly, income received was higher in waves 1, 2 and 4. Both participation and amount of income received remained lower in wave 6. Furthermore, more households indicated to be affected by lockdown effect in wave 6 as compared to wave 1 as shown in Figure 7.6. Total agricultural family labour was high in wave 5 and lowest in wave 2. High wage labour participation as well as family labour could be attributed to seasonality of agricultural farm activities given that wave 5 was conducted during the planting and growing phase of season one (main season) where there was a high demand of both family and hired labour for planting and other management activities such as weeding.

Concerning other variables, most of the households (56%) participated in financial related groups while only 17% belonged to a health or wellbeing group. There were variations in group participation across waves, with more people participating in groups overtime. For instance, participation in health-related groups rose by more than three times (from 7% in the baseline to 26.2 in wave 6). Only 4% of the households received income from loans while 5% of the households received remittances. Livestock value was high in wave 3 because of the survey was conducted during the festive season while asset value was high for wave 1 & 6. Roughly, 42.6% of the female owned at least one asset in households. Risk measures were collected only in the baseline, on average, 65 % of the households were risk averse, 9% were risk takers and 26 were risk neutral while labour coping strategies were collected in the last wave only.

**Primary outcome variables**

Approximately 69% of the total consumption expenditure was spent on food items. Average food consumption per capita was estimated at 78,727 UGX while non-food consumption value (excluding medical expenditures) was 34, 789 for the past two months. Food consumption value was higher in wave 1 and 2 while non-food consumption was higher in waves 4 and 5. Wave 1 was conducted during harvest period while wave 2 was a transition period (harvest & planting). Food and Agriculture Organization of the United Nations (2020a) reported an above-average production for the long rains season harvest in 2020 due to abundant rainfall, except for areas experiencing extremes. Wave 5 food consumption value was lower than other waves given that the period was a lean season while total and non-food consumption was low in both wave 1 and wave 6, partly attributed to COVID-19 lockdown measures. It seems the lockdown effect did not have a large effect on rural markets since at least over a half of the households indicated that major food staples, vegetables and fruits were always available in the local market in wave 1 and wave 6 despite the lockdown as shown in Figure 7.7.

On average, household diet diversity was 7. However, there exists tremendous regional differences in the number of food groups consumed. While total food counts were 8 for Kole, Lira, Bududa and Sironko districts, households in Moroto and Kisoro consumed 6 food groups while Kotido diet diversity was 5 (as shown in Figure 4.5). These three districts are the poorest among the sampled districts. Moreover, more food groups were consumed in wave 2 in most districts because the survey was conducted after the harvest main season. Matooke (cooking bananas), is a traditional and an important food crop for all regions, except in the Northern region while cassava is grown in most regions except in the Western (Mejia-Mantilla & Hill, 2017). Other common food crops include maize and beans which are grown and consumed in every region, while rice, soya beans, groundnuts, sweet potatoes and horticultural crops are common in most but not all regions. Coffee, tea, sugarcane, cocoa and tobacco are the main cash crops (Tesfaye & Tirivayi, 2020).

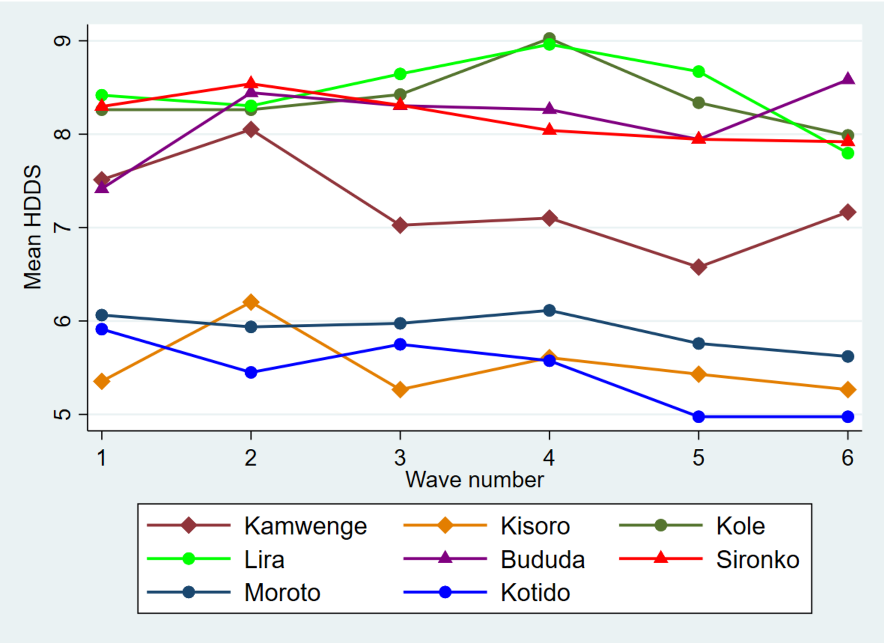


**Figure 4.5**: Household diet diversity across sampled districts for the six waves

Figure 4.6 shows the food groups consumed by sampled respondents. Rural households relied mostly on food crops as compared to livestock products. Over 80% of households consumed cereals, legumes, pulses and vegetables while consumption of starch foods/roots/tubers was slightly lower than the mentioned. This is consistent with Mottaleb et al. (2021) who reported that cereal consumption has been on the rise in the country and projects that consumption of cereals especially maize, wheat and rice will continue to rise due to the projected increase in population and income by 2030. On the other hand, consumption of traditional foods (matooke, cassava and sweet potatoes) has been on a decline. On average, utmost 40% of households consumed meat in the last 7 days while 17%, 11% and 29% ate fish or fish products, eggs and milk products respectively. The average share of animal source food value from all animal products out of total food consumption was only 12%.

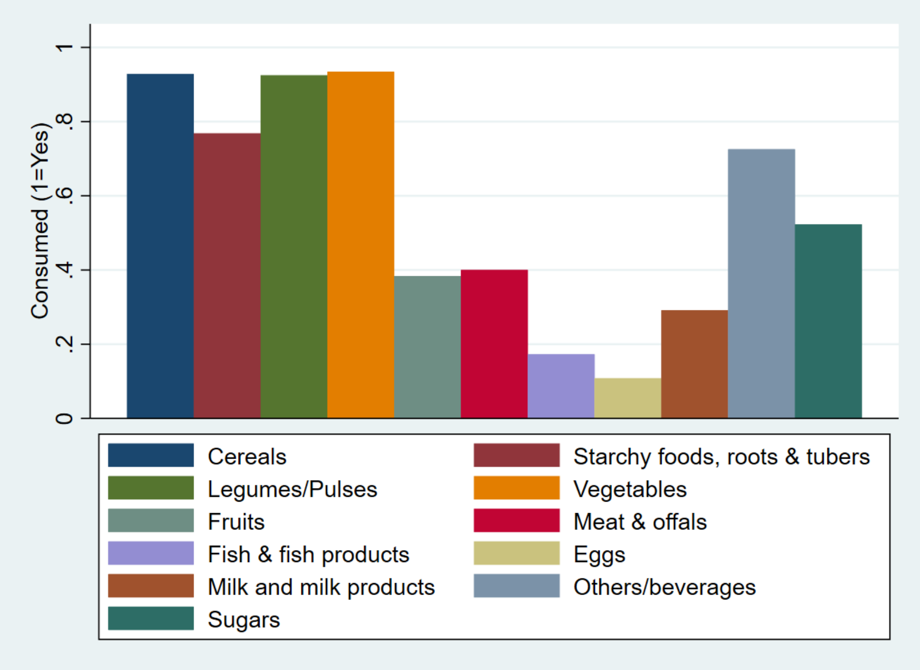


**Figure 4.6**: Food groups consumed by households in Uganda

**Consumption mobility**

In order to assess consumption mobility and persistence of poverty across different waves, we tabulate consumption matrices across 5 classes (quintiles) of the total consumption distribution for the different survey rounds. The 5*5 consumption transition matrices indicate the probabilities of movement between different quintile classes from wave 1 and wave 6, and from each of the t period to t+1 period as follows; wave 1 & 2, wave 2 & 3 wave 3 & 4, wave 4 & 5 and wave 5 &6 as shown in Table 4.3. Each of these transition matrices is computed from the distribution of logarithm value of per capita total consumption since we use the log values in empirical analysis. The figures on the diagonal of each matrix indicate percentage of households that remained in that quintile while the off-diagonal figures report consumption mobility.

Table 4.3 indicate that 51% of households in poverty (quintile 1) in wave 1 remained in poverty in wave 6 while 49% of the households initially in lower quintile moved out of poverty in wave 6. This is almost similar to mobility trends from wave 1 to wave 2 where 50% of households in poverty in wave 1 remained in poverty in wave 2 while 50% of the households initially in lower quintile moved to higher consumption quintiles in wave 2. Majority of these households moved to quintile 2 (21%) and quintile 3 (15%). Similarly, half of the households in the top quintile (5) in wave 1 remained in this class in wave 2 while 5% moved into poverty (quintile 1). There was substantial consumption mobility for the remaining middle consumption classes given that only 25-27% of the households initially in quintiles 2, 3 and 4 did not change quintiles in wave 2.

**Table 4.3**: Resilience assessment: Total consumption transition matrix (%)

| | Wave 1 & wave 6 | | | | | | Wave 1 & 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintiles | Wave 6 | | | | | Quintiles | Wave 2 | | | | |
| Wave 1 | 1 | 2 | 3 | 4 | 5 | Wave 1 | 1 | 2 | 3 | 4 | 5 |
| 1 | 51 | 26 | 14 | 5 | 5 | 1 | 50 | 21 | 15 | 8 | 6 |
| 2 | 23 | 30 | 24 | 18 | 6 | 2 | 33 | 27 | 22 | 11 | 7 |
| 3 | 17 | 21 | 27 | 30 | 6 | 3 | 9 | 27 | 25 | 27 | 12 |
| 4 | 6 | 12 | 25 | 27 | 30 | 4 | 4 | 16 | 28 | 27 | 24 |
| 5 | 3 | 11 | 10 | 21 | 54 | 5 | 5 | 10 | 10 | 26 | 50 |
| | Wave 2 & 3 | | | | | | Wave 3 & 4 | | | | |
| | Wave 3 | | | | | | Wave 4 | | | | |
| Wave 2 | 1 | 2 | 3 | 4 | 5 | Wave 3 | 1 | 2 | 3 | 4 | 5 |
| 1 | 55 | 24 | 14 | 6 | 1 | 1 | 64 | 21 | 6 | 8 | 2 |
| 2 | 26 | 30 | 25 | 10 | 10 | 2 | 19 | 35 | 25 | 15 | 5 |
| 3 | 15 | 23 | 23 | 28 | 10 | 3 | 10 | 20 | 34 | 26 | 10 |
| 4 | 3 | 15 | 24 | 26 | 31 | 4 | 4 | 17 | 23 | 31 | 25 |
| 5 | 1 | 7 | 13 | 31 | 48 | 5 | 2 | 6 | 12 | 20 | 59 |
| | Wave 4 & 5 | | | | | | Wave 5 & 6 | | | | |
| | Wave 5 | | | | | | Wave 6 | | | | |
| Wave 4 | 1 | 2 | 3 | 4 | 5 | Wave 5 | 1 | 2 | 3 | 4 | 5 |
| 1 | 59 | 26 | 10 | 3 | 2 | 1 | 70 | 23 | 3 | 2 | 1 |
| 2 | 24 | 33 | 27 | 10 | 6 | 2 | 22 | 35 | 27 | 13 | 3 |
| 3 | 10 | 20 | 30 | 28 | 12 | 3 | 5 | 27 | 37 | 24 | 7 |
| 4 | 4 | 19 | 23 | 31 | 23 | 4 | 1 | 12 | 23 | 34 | 30 |
| 5 | 3 | 2 | 10 | 27 | 56 | 5 | 2 | 3 | 9 | 27 | 59 |

Similar trend in dynamics of consumption was observed in other waves. However, results indicate that a higher proportion of households in the bottom quintile did not change the quintile in the subsequent waves, especially for the last survey rounds. For instance, 70% of the households in the lowest quintile class in wave 5 remained in this class in wave 6 while the remaining moved in the 2$^{nd}$ quintile. Correspondingly, a higher proportion of households in the top quintile (59%) in wave 5 remained in that quintile in wave 6 and at least a third in 2nd, 3rd and 4th quintile did not change quintiles in wave 6. In summary, results indicate a higher economic uncertainty in the initial waves given high consumption mobility as compared to the later waves.

Household diet diversity consumption matrix also shows similar pattern, with relatively more households remaining in the poor quintiles overtime. For instance, 67% of households who were in the poorest quantile in wave 1 were still poor in the sixth wave as shown in Table 4.4. In wave 5, almost three quarters of households who were in the bottom quintile in wave 4 remained poor. These results are consistent with (Chambers, 1982) who argued that lean period is the most difficult time in the year, where the poor are at their poorest, and many people are vulnerable of becoming poor. Indeed, 33% and 14% of households who were in the second and third quintile in wave 4 become poorer in wave 5.

**Table 4.4**: Resilience assessment: HDDS transition matrix (%)

| | Wave 6 | | | | | | Wave 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Wave 1 | 1 | 2 | 3 | 4 | 5 | Wave 1 | 1 | 2 | 3 | 4 | 5 |
| 1 | 67 | 19 | 11 | 3 | 1 | 1 | 53 | 38 | 5 | 1 | 2 |
| 2 | 29 | 20 | 34 | 10 | 8 | 2 | 24 | 31 | 23 | 12 | 10 |
| 3 | 17 | 10 | 41 | 18 | 14 | 3 | 8 | 26 | 25 | 19 | 22 |
| 4 | 11 | 13 | 37 | 18 | 22 | 4 | 1 | 17 | 20 | 30 | 31 |
| 5 | 6 | 6 | 35 | 21 | 33 | 5 | 3 | 17 | 17 | 15 | 49 |
| | Wave 3 | | | | | | Wave 4 | | | | |
| Wave 2 | 1 | 2 | 3 | 4 | 5 | Wave 3 | 1 | 2 | 3 | 4 | 5 |
| 1 | 57 | 33 | 7 | 3 | 0 | 1 | 67 | 25 | 4 | 3 | 1 |
| 2 | 31 | 38 | 17 | 7 | 6 | 2 | 21 | 42 | 19 | 14 | 4 |
| 3 | 13 | 34 | 20 | 19 | 15 | 3 | 6 | 26 | 24 | 21 | 23 |
| 4 | 3 | 14 | 28 | 24 | 30 | 4 | 3 | 11 | 23 | 23 | 40 |
| 5 | 5 | 18 | 17 | 26 | 34 | 5 | 3 | 8 | 15 | 21 | 53 |
| | Wave 5 | | | | | | Wave 6 | | | | |
| Wave 4 | 1 | 2 | 3 | 4 | 5 | Wave 5 | 1 | 2 | 3 | 4 | 5 |
| 1 | 74 | 14 | 10 | 1 | 1 | 1 | 67 | 20 | 10 | 3 | 0 |
| 2 | 33 | 26 | 31 | 8 | 2 | 2 | 38 | 22 | 30 | 4 | 4 |
| 3 | 14 | 12 | 45 | 16 | 12 | 3 | 10 | 16 | 45 | 17 | 12 |
| 4 | 12 | 11 | 36 | 27 | 13 | 4 | 7 | 7 | 45 | 21 | 20 |
| 5 | 1 | 3 | 26 | 27 | 44 | 5 | 0 | 3 | 31 | 24 | 43 |

**Poverty transitions and household factors associated with poverty transitions**

Table 4.5 shows the extent (number of times) and percentage of households experiencing poverty out of the six times the households were visited. A household is characterized as poor if it’s in the bottom most quintile (20 percent with the lowest total consumption per capita), and those in the topmost quintile are categorized as rich. Almost 57% of the households did not experience poverty in any of the waves. Only 4% of the households were chronically poor over the six rounds and 40% were sometimes poor with consumption levels in the lowest quintile, at least once over the survey period. These poverty levels are lower than those reported by Radeny et al. (2012) for Kenya where households who were never poor in Kenya were almost half (32%) while 11% were consistently poor over the four years. Similarly, over 50% of households were never in the top quintile while only 3% were always rich as shown in Table 4.5. The above findings indicate that consumption poverty and richness were not chronic but rather transitory.

**Table 4.5:** Distributions of households experiencing different periods of poverty (Q1) and richness (Q5)

| Bottom quintile (Q1) | | | Top Quintile (Q5) | | |
|---|---|---|---|---|---|
| Number of times (waves) | Freq. | Percent | Number of times | Freq. | Percent |
| 0 (always non- poor) | 352 | 57 | 0 | 325 | 52 |
| 1 | 88 | 14 | 1 | 113 | 18 |
| 2 | 53 | 9 | 2 | 66 | 11 |
| 3 | 41 | 7 | 3 | 36 | 6 |
| 4 | 26 | 4 | 4 | 35 | 6 |
| 5 | 37 | 6 | 5 | 25 | 4 |
| 6 (always poor) | 24 | 4 | 6 (always rich) | 21 | 3 |
| Total | 621 | 100 | | 621 | 100 |

We further explored the transition patterns between two survey rounds (not consecutive) with household characteristics, livelihoods and shocks that categorize four different types of households, namely; always poor, non-poor, those that exited poverty and those that descended into poverty. The latter two categories fall into the larger group of transiently poor. For example, households that exited poverty between wave 1 and 6 are those that were poor in the initial period (wave 1), but were nonpoor (in quintiles 2-5) in the final wave (6) while vice versa is true for those that descended into poverty.

We only focus on transition between defined two time periods rather than for the whole survey period. Furthermore, even though it would be interesting to focus on the households that experienced extreme transitions (i.e. from Q1 to Q5) and vice versa, the percentage of these households is very minimal as shown in the transition matrices. Table 4.6 presents characteristics of households based on their poverty transitions status considering wave 1 and wave 6. Households who were consistently non-poor accounted for the majority (70%) of sampled households. These households had higher asset values and higher wage income in both surveys' rounds. A large proportion participated in different types of groups, with a significant increase in participation in wave 6. In addition, they had better diet quality in terms of food groups consumed and at least 7% received remittances. On average, this welfare group received adequate rainfall and temperatures were colder than the mean. However, majority of households experienced health shocks in terms of sickness and high health costs as compared to other categories. This could be partly attributed to the low proportion accessing free medical services.

**Table 4.6:** Selected households characteristics by poverty transition, wave 1 and Wave 6

| Variables | Non- poor in both | | Poor in both | | Exited poverty | | Descended in poverty | |
|---|---|---|---|---|---|---|---|---|
| | **Wave 1** (N= 435 | **Wave 6** (N= 435) | **Wave 1** (N= 64) | **Wave 6** (N= 64) | **Wave 1** (N=61) | **Wave 6** (N=61) | **Wave 1** (N =61) | **Wave 6** **(N=61)** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Household size | 6.5 (2.5) | 6.6 (2.7) | 7.1 (2.3) | 7.0 (2.5) | 7.1 (2.0) | 6.3 (2.4) ** | 6.4 (1.9) | 6.5 (2.1) |
| Asset value (UGX) | 7,152,754 (12,758,928) | 7,546,063 (12,880,250) | 904,414 (1,059,675) | 746,195 (861,813) | 1,994,138 (3,511,175) | 2,561,959 (3,880,498 | 1,496,680 (2,631,186) | 1,116,877 (1,869,669) |
| Female asset ownership (%) | 36 | 30* | 70 | 72 | 44 | 33\| | 64 | 67 |
| Livestock value (UGX) | 1,605,548 (2,653,280) | 1,736,056 (2,457,964) | 2,000,406 (5,709,758) | 1,461,719 (2,905,317) | 1,158,459 (2,428,138) | 1,326,262 (1,930,399) | 2,697,402 (4,968,137) | 1,302,164 (2,576,005) * |
| Membership any group (%) | 74 | 83*** | 31 | 39 | 62 | 85*** | 42 | 31 |
| Health or wellbeing group (%) | 9 | 30*** | 0 | 8** | 8 | 36*** | 2 | 10* |
| Financial group (%) | 50 | 69*** | 19 | 25 | 41 | 57* | 26 | 16 |
| Loan income (%) | 2.1 | 4* | 3.1 | 0 | 3 | 2 | 3 | 3 |
| Remittances (%) | 9 | 7 | 2 | 0 | 3.3 | 6.6 | 3.3 | 1.6 |
| Wage labor participation (%) | 65 | 64 | 44 | 22*** | 54 | 57 | 36 | 26*** |
| Wage income (UGX) | 251,300 (647929) | 272, 433 (577, 946) | 80, 078 (142,158) | 24, 734 (93, 174) *** | 106, 803 (195, 391) | 106, 697 (169,220) | 140, 382 (183,648) | 26,500 (86,175) *** |
| Household diet diversity | 7.73 (1.78) | 7.57 (2.08) | 5.33 (1.39) | 4.98 (1.21) | 5.51 (1.69) | 6.03 (1.51) * | 6.48 (1.85) | 4.84 (1.28) *** |
| Rainfall Z scores (2 months) | 0.035 (0.696) | -0.513 (0.922) *** | -0.822 (0.393) | -0.989 (0.345) ** | -0.399 (0.619) | -1.062 (0.647) *** | -0.551 (0.532) | -0.878 (0.457) *** |
| Temperature Z scores (2 months) | -0.376 (0.752) | -0.106 (1.068) *** | 0.456 (0.651) | 1.057 (0.722) *** | -0.225 (0.787) | 0.316 (1.047) *** | 0.130 (0.766) | 0.652 (0.921) *** |
| Extreme temperature (%) | 0 | 14*** | 13 | 64 *** | 0 | 30*** | 3 | 49*** |
| HHs member sick (%) | 72 | 69 | 67 | 39*** | 77 | 48*** | 64 | 44** |
| HHs number of sick days | 17 (24) | 11 (14) *** | 10 (14) | 3(6) *** | 15 (18) | 5 (9) *** | 10 (16) | 4 (6) *** |
| Member sick more than 30 days (%) | 10 | 6.2** | 9 | 2* | 8 | 0** | 8 | 2* |
| HH hospitalized (1=Yes) | 12 | 12 | 13 | 5 | 21 | 5*** | 11 | 7 |
| Death of hhs member (%) | 0.5 | 1.1 | 1.6 | 0 | 1.6 | 1.6 | 0 | 1.6 |
| Total health expenditures (UGX) | 62,021 (201,248) | 52,734 (146,241) | 9,563 (25,864) | 2, 531* (15,193) | 35,840 (64,817) | 15, 811 ** (34,864) | 11,523 (25, 081) | 8,361 (30,625) |
| Free medical services (%) | 17 | 12** | 52 | 30** | 28 | 13** | 41 | 26* |

The figures in the parenthesis are standard deviations. For continuous variable, t-test is used to test if there are significance differences between two time periods for each category of households. Pearson chi2 test is used for dummy variables

Only 10% of the households were poor in both wave 1 and 6. These households are categorized by lower asset values but higher livestock values. Over two thirds of women in these households owned at least an asset and it could be possible that most of these households were widowed.

Participation in group networks was lower and very few households received remittances. Furthermore, participation in wage employment was lower translating into lower mean wage income, which further decreased significantly from wave 1 to wave 6, impacting food diversity. These households consistently received rainfall below the long-term mean and temperatures were higher than the mean in both periods. In fact, over 60% of households experienced temperature above 1 standard deviation from the mean in wave 6. Though poor health was one of the major shocks, there was a significant decline in health indicators and health expenditures over time. Majority of households in this welfare group relied on free medical services. Similar characteristics of non-poor and poor households in other two pairs of waves (wave 2 and wave 4) and (wave3 and wave 6) are reported as shown in Table 7.18 of the appendix.

Households that transited upwards or downwards accounted for 20% of total sample as shown in Table 4.6. Households exiting poverty recorded a significant reduction of household members from wave 1 to wave 6. In general, this welfare group exhibited an increase in assets and livestock. Furthermore, there was a significant increase in participation in group networks and household diet diversity. Even though they experienced cooler temperatures at the start of the survey in wave 1, and a little bit of rainfall shortfalls, at least a third of households experienced temperature greater than the long-term in wave 6. Since wave 6 was conducted during dry season, we presume that temperatures did not have major implications on plant growth rather necessary for drying of crops. There was also a significant drop in sickness and health expenditures, reducing the cost and productivity burden on these households, thus improved welfare.

Households descending into poverty experienced significant reduction in their livestock value. Even though household size, assets and participation in groups remained relatively steady in the two periods, there was a significant reduction in wage labour participation and average wage income as shown in Table 4.6. This partly explains the significant reduction in diet quality. Furthermore, households experienced rainfall lower than long-term mean in both waves with significant shortfalls in wave 6 while temperatures were above the mean. A high share of households experienced health shocks in wave 1 which declined significantly in wave 6. Nevertheless, the reduction in health expenditures was insignificant and some households a death of a household member that could potentially translate to worse welfare.

Table 4.7 shows households characteristics, livelihood strategies and shocks for households that escaped and descended into poverty for other waves. Generally, the results are similar to the earlier reported, with households escaping poverty recording an increase in assets and livestock over the two time periods while those descending into poverty showing a decline. Even though there was an increase in proportion of households that belonged to a group network for those exiting poverty, the differences were insignificant. A significant decrease in group membership was observed on households that descended into poverty between wave 1 and wave 6.

**Table 4.7**: Selected households characteristics by poverty transition – transient poverty (wave 2 and Wave 4), and (wave 3 and 6)

| **Variables** | **Exited poverty** | | **Exited poverty** | | **Descended in poverty** | | **Descended in poverty** | |
|---|---|---|---|---|---|---|---|---|
| | **Wave 2** (N=65) | **Wave 4** (N=65) | **Wave 3** (N= 45) | **Wave 6** (N= 45) | **Wave 2** (N =65) | **Wave 4** **(N=65)** | **Wave 3** (N = 45) | **Wave 6** **(N= 45)** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Household size | 7.76 (2.76) | 7.18 (2.96 | 8.22 (2.59) | 6.68 (2.80) *** | 6.89 (2.11) | 7.01 (2.17) | 7.11 (3.09) | 6.75 (2.76) |
| Asset value | 1,912,554 (3,294,797) | 2,661,777 (4,013,218) | 1,768,856 (1,767,250) | 1,557,711 (1,352,456) | 1,834,062 (1,961,368) | 1,474,908 (1,452,885) | 1,738,422 (4,517,828) | 1,247,267 (1,920,297) |
| Asset ownership (1= Female) | 46 | 48 | 42 | 31 | 62 | 58 | 56 | 60 |
| Livestock value | 1,486,015 (2,594,434) | 1,637,462 (1,969,388) | 1,493,822 (2,497,109) | 2,110,822 (3,116,878) | 1,347,332 (2,620,664) | 1,222,046 (2,222,856) | 2,041,844 (2,365,428) | 1,554,267 (323,3456) |
| Membership any group (%) | 75 | 79 | 73 | 78 | 75 | 72 | 69 | 49* |
| Health or wellbeing group (%) | 2 | 6 | 24 | 31 | 8 | 29*** | 4 | 7 |
| Financial group (%) | 51 | 65 | 44 | 51 | 46 | 45 | 49 | 38 |
| Loan income (%) | 2 | 3 | 2 | 0 | 5 | 5 | 7 | 2 |
| Remittances (%) | 3 | 6 | 4 | 9 | 0 | 5* | 2 | 2 |
| Paid labor force participation (%) | 43 | 38 | 55 | 69 | 63 | 34*** | 29 | 20 |
| Wage income (UGX) | 91,662 (193,113) | 96, 512 (239, 767) | 132, 988 (244, 398) | 127, 677 (194, 519) | 130,514 (215,032) | 44, 508 (93, 498) *** | 47, 455 (117, 070) | 22, 788 (99, 168) |
| Household diet diversity | 5.892 (1.50) | 7.03 (1.984) *** | 5.86 ( 1.57) | 6.4 (1.84) | 6.45 (1.639) | 5.354 (1.452) *** | 6.91 (1.50) | 5.4 (1.47) *** |
| Rainfall Z scores (2 months) | 0.827 (1.387) | -0.298 (1.218) *** | 0.709 (1.387) | -0.942 (0.781) *** | -0.174 (1.556) | 0.347 (1.699) * | -0.296 (1.164) | -0.864 (0.448) *** |
| Temperature Z scores (2 months) | -0.179 (0.786) | 0.228 (1.021) ** | -0.460 (0.871) | 0.084** (1.144) | -0.349 (0.856) | -0.225 (1.115) | 0.371 (0.605) | 0.966 (0.670) *** |
| Extreme temperature (%) | 0 | 29*** | 2 | 22*** | 0 | 25*** | 13 | 60*** |
| HHs member sick (%) | 83 | 82 | 78 | 56** | 74 | 58* | 76 | 49*** |
| HHs number of sick days | 15 (16) | 20 (28) | 15.2 (16.4) | 8.3 (9.7) ** | 14 (19) | 9 (16) | 13.4 (19.6) | 4.6 (6.8) *** |
| HH member sick more than 30 days (%) | 12 | 17 | 16 | 0*** | 12 | 9 | 11 | 2** |
| HH member sick & admitted (%) | 14 | 17 | 22 | 7** | 20 | 9* | 22 | 9* |
| Death of hhs member (%) | 2 | 5 | 0 | 7* | 2 | 6 | 7 | 2 |
| Total health expenditures (UGX) | 23, 601 (66,171) | 41, 994 (147,753) | 37,499 (59,882) | 32,435 (116,915) | 31, 487 (68,337) | 12, 479 (22,761) ** | 42, 886 (86,368) | 10, 756 (35, 167) ** |
| Free medical services | 43 | 35 | 27 | 18 | 45 | 20*** | 33 | 26 |

The table further highlights the importance of health shocks and wage income with movement overtime. For instance, households escaping poverty between wave 3 and 6 experienced a significant decline in sickness, and increased consumption of food groups between wave 2 to wave 4. On the other hand, those falling into poverty recorded a significant decline in wage income.

### 4.3.4 Empirical framework

The primary outcomes of the study are continuous variables; food, non-food consumptions and total consumption per capita. We also consider household dietary diversity as a measure food quality. Our dataset is longitudinal collected over six time periods, therefore we adopt panel estimators. As a starting point we estimate the relationship between changes in these outcome variables with changes in weather, illness and changes in the interaction of both weather and illness. In this way, we are able to determine if the hypothesized relationship exist, before explaining the mechanisms through which these effects occur. The generic specification of panel data model is as follows, where $i$ indexes household and $t$ time period;

$$C_{it} = \alpha + \beta_1 H_{it} + \beta_2 W_{it} + \beta_3 W_{it} * H_{it} + \beta_4 X_{it} + \beta_5 S_{it} + \varepsilon_{it} \qquad 4.1$$

Where $C_{it}$ is consumption value for household $i$ for time $t$ regressed against health measures ($H_{it}$) and extreme weather events ($W_{it}$) for a given household. Health measures include both dummies variables (whether any household was admitted or if a member had illness that lasted more than 30 days) and the count of number of sick days household members were sick. Weather variables include extreme high rainfall and extreme high temperature (dummy variables) developed from z scores of both rainfall and temperature, based on two months rolling averages of weather in the actual recall period and historical mean corresponding to the months in the recall period. Our main coefficient of interests is on the interaction term $\beta_3$ which indicates the effect of health outcomes on consumption based on weather characteristics. Additionally, coefficients $\beta_1$ and $\beta_2$ on health and weather shocks are of interest to the study. All our explanatory variables of interest are time varying. $X_{it}$denotes time variant characteristics such as assets and livestock value among others. Different self and mutual insurance consumption mechanisms are denoted by $S_{it}$ and they include social networks (membership in groups), access to loans, remittances and free medical services. Error term is denoted by $\varepsilon_i$ which captures household specific unobserved component.

We fit the above estimation using fixed effects (within estimator) which strictly excludes time invariant variables. The time constant variables are removed through the subtraction process. In our case, demeaned household consumption is regressed on demeaned time variant covariates as shown below;

$$C_{it} - \overline{C_\imath} = \alpha + \beta_1 (H_{it} - \overline{H_\imath}) + \beta_2 (W_{it} - \overline{W_\imath}) + \beta_3 (W_{it} * H_{it} - \overline{W_\imath * H_i}) + \beta_4 (X_{it} - \overline{X_\imath}) + \beta_5 (S_{it} - \overline{S_\imath}) + (\varepsilon_{it} - \varepsilon_i) \qquad 4.2$$

Time demeaning eliminates individual specific unobserved effects which might be correlated with other independent variables in the model. The ability to overcome omitted variable bias, and obtain consistent estimators is one attractive advantage of using fixed effects model. Furthermore, its documented that fixed effects model is more robust than other panel data methods such as pooled OLS and random effects (Wooldridge, 2002). The latter model has strong assumptions of zero correlation between individual unobserved effects and observed explanatory variables (Wooldridge, 2002). In general, panel data methods result into more efficient estimators than cross-section because of more variation provided by the datasets and less multicollinearity issues (Hsiao, 2007). However, we also conduct multicollinearity tests among the explanatory variables by use of variance inflation factor (VIF). A mean VIF of 1.41 estimated in consumption modules indicates that our explanatory variables are less correlated.

For robustness checks and to establish effect of time-invariant variables such as risk preferences, we estimate a first difference model. We also include other factors such as baseline household head characteristics (age, sex, education and occupation), included in consumption and health models. Community dummies which captures changes in community consumption values and considers other covariate shocks at community level are also incorporated. The specification for first difference model is as follows;

$$\Delta C_i = \alpha + \beta_1 \Delta H_i + \beta_2 \Delta W_i + \beta_3 \Delta W_i * \Delta H_i + \beta_4 \Delta X_{1i} + \beta_5 \Delta S_i + \beta_6 X_{2i}\ \varepsilon_i \qquad 4.3$$

Where $\Delta C_i$ is the change in consumption over two time periods (t and t+1), other variables remain as earlier defined with changes of covariates over two time period. Variables that change slowly over time or time invariant observables are denoted by $(X_{2i})$. Both fixed effects and first difference models are unbiased and consistent though they yield different coefficient when time is greater than 2. The standard first differencing estimator also helps in addressing the problem of omitted variables. Especially the bias due to time invariant unobservable. Furthermore, differencing outcome variables may eliminate biases due to measurement errors under certain conditions (Liker et al., 1985). We use first difference model since it has widely been used previously in estimating effects of health shocks on consumption. Furthermore, Asfaw and von Braun (2004) argue that differencing health indicators, helps reducing biases associated with measurement errors inherent in self-reported health measures as well as predictability of some health conditions.

We repeat these estimations with household diet diversity as a dependent variable and use fixed effect Poisson model. In Equation 4.1, we treated health as an exogeneous variable, however health may be endogenous in explaining consumption, and also not random. There might be a possibility of reverse causality between health and food consumption, and selection bias. Even though we suspect the feedback to be unlikely given the differences in recall period and some of endogeneity issues addressed by fixed effect estimator, we repeat the above estimation with fixed effect instrumental variable estimator where health is instrumented with weather variables (temperature in the last two months and its quadratic term), in order to address any endogeneity concerns as well isolate the effect of weather-induced health on consumption. The specification is as follows;

$$C_{it} = \alpha + \beta_1 \widehat{H}_{it} + \beta_2 W_{it} + \beta_4 X_{it} + \beta_5 S_{it} + \varepsilon_i \quad (4.4)$$

$$H_{it} = \alpha + \beta_2 W_{it} + \beta_4 X_{it} + \beta_5 S_{it} + \beta_6 Z_{it} \varepsilon_i \quad (4.5)$$

The variables remain as earlier defined, $\widehat{H}_{it}$ is the instrumented health variable, $\beta_1$ is our coefficient of interest and $Z_{it}$ represents the instruments.

There are several mechanisms through which the effect of weather-related illness on consumption may occur. For instance, illness may increase medical expenditures causing re-allocation of resources planned for consumption on health care services. Furthermore, illness may reduce participation in labour force, reduced working hours thus lower household earnings and labour productivity. In order to establish this linkage, we estimate the following equation with medical expenditure, labour and earnings as the dependent variables.

$$L_{it} = \alpha + \vartheta_1 H_{it} + \vartheta_2 W_{it} + \vartheta_3 W_{it} * H_{it} + \vartheta_4 X_{it} + \varepsilon_i \quad (4.6)$$

The explanatory variables remain as earlier explained in previous equations. $L_{it}$ represents either wage labour income, health expenditures and family agricultural labour supply in terms of person days. Coefficient of interest is on the interaction term consisting of weather and health variables ($\vartheta_3$) as well as on health and weather covariates ( $\vartheta_1$ & $\vartheta_2$). Since a substantial proportion of households did not report any wage labour income and health expenditures we fit the above equation using panel random effects Tobit model and fixed effects for person days.

In order to explore the effect of our main explanatory variables on the entire distribution of our main response variables (consumption), we adopt panel quantile regressions methods including individual effects. Quantile regressions ($Q_y$ $(\tau \mid X)$ enables examination of the distributional and heterogeneous effects across different quantiles and are more suitable in presence of outliers (Ike et al., 2020). The method is particularly informative given that it can be used to estimate effects at any quantile of distribution based on the interest of the researcher rather than the least square and other methods that focus on the average effects (Lamarche, 2021). Panel quantile methods are more recent, first introduced by Koenker (2004). In this study, we employ fixed effects Method of Moments Quantile Regression (MMQR) proposed by Machado and Silva (2019), effective for panel data models. The model is advantageous in estimation of regression quantiles that don't cross, allows individual effects to have an effect on the entire conditional distribution and is computational easier to implement even when the regressors are many and large sample size as compared to other quantile methods (Machado and Silva 2019). The main limitation is that it requires a larger T.

Since Machado and Silva (2019) quantile regression estimator (xtqreg) is an extension of fixed effects model (xtreg), we conduct heterogeneity analysis only on estimations where fixed effects model is used. We consider four quantiles (0.2, 0.4, 0.6 and 0.8) in order to establish the hypothesized relationship in the poorest quantile, consumption smoothing mechanisms used by the poor and the quantile in which the negative effect of weather-related shocks on consumption are pronounced.

Lastly, we attempt to estimate the effect of food consumption on health by estimating the following equation with lagged consumption ($C_{i\,(t-1)}$ ) as the main explanatory variable.

$$H_{it} = \alpha + \beta_1 C_{i\,(t-1)} + \beta_2 W_{it} + \beta_{2a} W_{i(t-1)} + \beta_3 W_{i(t-1)} * C_{i\,(t-1)} + \beta_4 X_{it} + \beta_5 S_{it} + \varepsilon_{it} \tag{4.7}$$

Lagged consumption is used because of the differences in recall period, therefore consumption in a specific survey round were unlikely to affect health in that particular round. In addition, we incorporate both the current and lagged weather shocks ($W_{it}$), and the interactions between lagged consumption and lagged weather variables ( $W_{i(t-1)} * C_{i\,(t-1)}$) on the right-hand side of the equation 4.7. The use of lags on the main explanatory variable minimizes endogeneity issues in the above estimation.

Given that the dependent variable ( $H_{it}$ ) in the above equation is total days of illness at household level, we use Poisson regressions. Specifically, the Poisson pseudo maximum likelihood (PPML) with multiple high-dimensional fixed effects (HDFE) that not only accounts for the count nature of the variable but also addresses the problem of zero values on the dependent variable (Correia et al., 2020), which are dropped in the traditional Poisson regression. On average, approximately a third of households did not record any sickness (0 days of illness). The model is attractive because of less assumptions, provides consistent and valid estimates even in the presence of heteroskedasticity and controls for panel fixed effects since it allows usage of factorial variables (Correia et al., 2020).

## 4.4 Empirical Results

Our primary focus is to establish the link between extreme weather, illness and both shocks on consumption. However, before we present our main findings, we report results on the effect of weather and illness on consumption without the interaction terms or instruments, as a starting point. We also control for other covariates in all our estimations. Fixed effects results in Table 7.19 show that even though illness as measured by household member sick more than 30 days did not have significant effects on total and food consumption, this health measure reduced non-food consumption significantly. The results suggest that having a household member sick more than 30 days over the past two months is associated with 8.8% reduction in non-food consumption. On the contrary, having a member hospitalized for at least one night on the account of illness increases non-food consumption by 8.7% as shown in columns 9, and total consumption by 4%. We do not find significant effects of hospitalization on food consumption while days of illness increased food consumption significantly, even though the magnitude was negligible. Associations between different illness measures and food consumption remain positive and insignificant in all other regressions.

On weather variables, results present a sizable, negative and significant effect of extreme high rainfall on all consumption measures. Weather shocks are presented with dummy variables, therefore negative coefficient indicates that households experiencing extreme rainfall higher than the norm reduced their consumption levels by around 13% for total consumption and food consumption while non-food consumption reduced by 11%. For temperature, the results are consistently negative and significant for total and non-food consumption where warming reduced non-food consumption by 19% and food consumption by 10%. There was no significant effect of low rainfall[27] on all consumption categories.

**Effect of illness, weather on consumption (with interactions)**

We now focus on our main regression results consisting of health shocks, weather shocks and the interactions of both shocks, holding other covariates constant. Results in Table 4.8 show that illness in terms of household sick days and if any member was sick more than 30 days did not have significant effect on total consumption, food and non-food consumption. However, the results of hospitalization are positive and significant for non-food consumption, with almost similar coefficient sizes reported in the previous analysis without interaction terms. Hospitalization increased non-food consumption significantly by 9% as shown in column 9.

Both extreme temperature and rainfall were detrimental to consumption as shown in Table 4.8. Occurrence of extreme rainfall reduced total consumption by 13-15% and food and non-food consumption by 11 -14%. Similarly, temperature reduced total consumption by 13-20%, food consumption by 10-18% and non-food consumption by up to 17%. One of our main explanatory variables is the interaction terms between weather and health shocks. The coefficients of the interaction terms between all health measures and extreme temperature on non-food consumption were negative and significant for the interaction terms between temperature and days of illness. This implies that households with both health shocks in terms of days of illness and extreme temperature were more likely to have reduced non-food consumption. On the contrary, the coefficients of the interaction terms between health shocks and extreme temperature were positive and significant on food consumption while the interaction terms between health shocks and rainfall measures were insignificant with mixed signs in the rest of the regressions.

We find relatively similar results in the first differenced model where interactions between health measures and temperature are consistently negative and significant for estimations consisting of sick days and days of illness.

[27] We remove this variable in the subsequent equations, in order to focus on the 2 extremes with an effect.

**Table 4.8**: Effect of health, weather shocks and their interactions on consumption (FE model)

| Variables | Total consumption | | | Food consumption | | | Non-food consumption | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| HHs member sick more than 30 days | -0.020 | | | 0.003 | | | -0.070 | | |
| | (0.033) | | | (0.033) | | | (0.057) | | |
| Days of illness | | 0.000 | | | 0.001 | | | -0.000 | |
| | | (0.001) | | | (0.001) | | | (0.001) | |
| Hospitalized | | | 0.041 | | | 0.027 | | | 0.087* |
| | | | (0.026) | | | (0.026) | | | (0.045) |
| Extreme rain | -0.130*** | -0.149*** | -0.131*** | -0.128*** | -0.144*** | -0.125*** | -0.112** | -0.136** | -0.122** |
| | (0.028) | (0.033) | (0.029) | (0.028) | (0.033) | (0.029) | (0.049) | (0.057) | (0.050) |
| Extreme temperature | -0.159*** | -0.198*** | -0.130*** | -0.126*** | -0.179*** | -0.101*** | -0.170*** | -0.123* | -0.170*** |
| | (0.035) | (0.038) | (0.035) | (0.035) | (0.038) | (0.035) | (0.061) | (0.066) | (0.061) |
| Sick 30days# extreme rain | -0.006 | | | -0.001 | | | 0.038 | | |
| | (0.085) | | | (0.085) | | | (0.147) | | |
| Sick 30days# extreme temp | 0.372*** | | | 0.406*** | | | -0.280 | | |
| | (0.104) | | | (0.103) | | | (0.180) | | |
| Days of illness# extreme rain | | 0.001 | | | 0.001 | | | 0.002 | |
| | | (0.001) | | | (0.001) | | | (0.003) | |
| Days of illness # extreme temp | | 0.008*** | | | 0.010*** | | | -0.008** | |
| | | (0.002) | | | (0.002) | | | (0.003) | |
| Hospitalized# extreme rain | | | -0.009 | | | -0.037 | | | 0.080 |
| | | | (0.065) | | | (0.065) | | | (0.112) |
| Hospitalized #extreme temp | | | 0.040 | | | 0.131 | | | -0.254 |
| | | | (0.104) | | | (0.104) | | | (0.180) |
| Household size | -0.124*** | -0.126*** | -0.123*** | -0.136*** | -0.138*** | -0.134*** | -0.098*** | -0.097*** | -0.101*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.016) | (0.016) | (0.016) |
| Assets value (log) | 0.087*** | 0.085*** | 0.086*** | 0.057*** | 0.055*** | 0.057*** | 0.124*** | 0.124*** | 0.122*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.020) | (0.020) | (0.020) |
| Livestock value (log) | 0.008*** | 0.008*** | 0.008*** | 0.011*** | 0.011*** | 0.011*** | 0.000 | 0.000 | 0.000 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) | (0.004) |
| Gender of assets owner | -0.000 | -0.001 | 0.001 | 0.005 | 0.003 | 0.005 | -0.045 | -0.042 | -0.041 |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.040) | (0.040) | (0.040) |
| Free medical services | 0.012 | 0.001 | 0.010 | 0.050** | 0.038* | 0.050** | -0.089** | -0.083** | -0.095** |
| | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.038) | (0.038) | (0.038) |
| Health related group | 0.030 | 0.030 | 0.028 | 0.029 | 0.029 | 0.028 | 0.049 | 0.047 | 0.041 |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.051) | (0.050) | (0.051) |
| Financial related group | 0.096*** | 0.094*** | 0.098*** | 0.069*** | 0.065*** | 0.071*** | 0.161*** | 0.165*** | 0.158*** |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.036) | (0.036) | (0.036) |

| | Total consumption | | | Food consumption | | | Non-food consumption | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Received loan | 0.072* | 0.068 | 0.065 | 0.060 | 0.055 | 0.052 | 0.145* | 0.147* | 0.142* |
| | (0.044) | (0.044) | (0.044) | (0.043) | (0.043) | (0.044) | (0.075) | (0.075) | (0.076) |
| Remittances | 0.070* | 0.071* | 0.066* | 0.000 | 0.002 | -0.003 | 0.184*** | 0.184*** | 0.181*** |
| | (0.040) | (0.040) | (0.040) | (0.040) | (0.040) | (0.040) | (0.069) | (0.069) | (0.069) |
| Individual fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 |
| R-squared | 0.118 | 0.120 | 0.115 | 0.135 | 0.139 | 0.132 | 0.110 | 0.111 | 0.111 |
| Number of HHID | 621 | 621 | 621 | 621 | 621 | 621 | 621 | 621 | 621 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Additionally, moving from healthy status to unhealthy status in terms of hospitalization increases non-food consumption by 10% and total consumption by almost 5% as shown in Table 7.20. Extremely above than average rainfall reduced all consumption categories significantly while temperature reduced food and non-food consumption. The advantage of the first differenced model is that it allowed us to report the coefficients of time invariant variables of interest such as risk variables and community variables. Results in Table 7.20 shows that risk takers were more likely to consume more food by 3% while risk neutral households were associated with increased non-food consumption by 5%, as compared to the risk averse households. Community variables controls for other covariate shocks such as prices, not included in the model that are likely to affect consumption.

**Association between health and weather shocks on diet diversity**

Table 4.9 presents coefficients of interest in the household dietary diversity score (HDDS) regressions, both with and without interaction terms. Since the HDDS was a count, we present results of the fixed effects poison regression. Results are consistent with fixed effects regression on food consumption, where different measures of illness had a positive and insignificant effect on total count of food groups consumed by the households. The coefficient of days of illness are weakly significant at 10% significance level, with an opposite sign, implying that an increase in days of illness increased diet diversity. Extreme rainfall did not have significant effects on HDDS while temperatures had negative effect on diet diversity as shown in columns 4 and 5. Specifically, households experiencing extreme temperatures reduced diet diversity by 6% as compared to those who did not experience high temperature.

Results also show that an increase in livestock value was positively associated with diet diversity and participating in finance related groups increased consumption by 4%. For risk measures, first difference results[28] shows that there was no significant association between risk preferences and HDDS.

[28] These results are not shown, but available upon request.

**Table 4.9**: Effect of illness & weather on household diet diversity (FE Poisson)

| VARIABLES | Without interactions | | | With interactions | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HHs member sick more than 30 days | 0.023 | | | 0.017 | | |
| | (0.025) | | | (0.028) | | |
| Days of illness | | 0.001* | | | 0.001 | |
| | | (0.000) | | | (0.000) | |
| Hospitalized | | | 0.012 | | | 0.009 |
| | | | (0.020) | | | (0.022) |
| Extreme rain | 0.016 | 0.015 | 0.016 | 0.016 | 0.010 | 0.014 |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.028) | (0.025) |
| Extreme temperature | -0.048 | -0.047 | -0.046 | -0.056* | -0.063* | -0.047 |
| | (0.032) | (0.032) | (0.032) | (0.033) | (0.036) | (0.033) |
| Sick 30days# extreme rain | | | | 0.004 | | |
| | | | | (0.070) | | |
| Sick 30days# extreme temp | | | | 0.097 | | |
| | | | | (0.094) | | |
| Days of illness# extreme rain | | | | | 0.000 | |
| | | | | | (0.001) | |
| Days of illness # extreme temp | | | | | 0.002 | |
| | | | | | (0.002) | |
| Hospitalized# extreme rain | | | | | | 0.015 |
| | | | | | | (0.053) |
| Hospitalized #extreme temp | | | | | | 0.008 |
| | | | | | | (0.095) |
| Household size | -0.000 | -0.001 | -0.000 | -0.001 | -0.001 | -0.000 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Assets value (log) | 0.014 | 0.013 | 0.014 | 0.014 | 0.013 | 0.014 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Livestock value (log) | 0.005** | 0.005** | 0.005** | 0.005** | 0.005** | 0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Gender of assets_owner | -0.002 | -0.002 | -0.001 | -0.002 | -0.002 | -0.002 |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Free medical services | 0.019 | 0.014 | 0.020 | 0.019 | 0.013 | 0.020 |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Health_related_group | -0.035 | -0.034 | -0.035 | -0.035 | -0.034 | -0.035 |
| | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Financial_related_group | 0.039** | 0.039** | 0.039** | 0.039** | 0.039** | 0.039** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Received loan | 0.015 | 0.012 | 0.013 | 0.015 | 0.013 | 0.013 |
| | (0.038) | (0.038) | (0.038) | (0.038) | (0.038) | (0.038) |
| Remittances | -0.004 | -0.003 | -0.004 | -0.003 | -0.002 | -0.004 |
| | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) |
| Wave variable | Yes | Yes | Yes | Yes | Yes | Yes |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

### Heterogeneous effects of illness and weather on consumption

We further explored the distributional and heterogeneous effects of health and weather shocks and their interactions on the different categories of consumption using panel fixed effects quantile regression estimators. We only focus on total consumption and non-food consumption where some of our covariates of interest were significant, and report the 20th, 40th, 60th and 80th percentiles. Results in Table 4.10 shows negative and insignificant effect of illness (if household member was sick more than 30 days) across all quantiles except at the top quantile where the effect was positive and insignificant.

**Table 4.10**: Quantile FE results on effect of health, weather shocks and interactions on total and non-food consumption

| | Total consumption Quantile | | | | Non-food consumption Quantile | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | 0.2 | 0.4 | 0.6 | 0.8 | 0.2 | 0.4 | 0.6 | 0.8 |
| HHs member | -0.053 | -0.034 | -0.010 | 0.013 | -0.071 | -0.070 | -0.069 | -0.068 |
| sick > 30 days | (0.045) | (0.034) | (0.034) | (0.048) | (0.075) | (0.055) | (0.055) | (0.078) |
| Extreme rain | -0.129*** | -0.130*** | -0.131*** | -0.131*** | -0.123* | -0.116** | -0.108** | -0.100 |
| | (0.038) | (0.029) | (0.029) | (0.041) | (0.065) | (0.048) | (0.048) | (0.068) |
| Extreme | -0.151*** | -0.156*** | -0.162*** | -0.167*** | -0.162** | -0.167*** | -0.173*** | -0.179** |
| temperature | (0.045) | (0.034) | (0.034) | (0.049) | (0.082) | (0.061) | (0.061) | (0.087) |
| Sick 30days# | 0.026 | 0.007 | -0.015 | -0.037 | 0.061 | 0.047 | 0.030 | 0.013 |
| extreme rain | (0.100) | (0.075) | (0.075) | (0.107) | (0.192) | (0.142) | (0.142) | (0.201) |
| Sick 30days# | 0.270* | 0.331*** | 0.403*** | 0.476*** | -0.586* | -0.393* | -0.183 | -0.092*** |
| extreme temp | (0.161) | (0.121) | (0.122) | (0.173) | (0.316) | (0.235) | (0.234) | (0.023) |
| Household | -0.127*** | -0.125*** | -0.123*** | -0.120*** | -0.104*** | -0.100*** | -0.096*** | 0.041 |
| size | (0.013) | (0.010) | (0.010) | (0.014) | (0.022) | (0.016) | (0.016) | (0.332) |
| Assets value | 0.072*** | 0.081*** | 0.092*** | 0.103*** | 0.096*** | 0.113*** | 0.133 *** | 0.153*** |
| (log) | (0.016) | (0.012) | (0.012) | (0.018) | (0.028) | (0.021) | (0.021) | (0.030) |
| Livestock | 0.009*** | 0.008*** | 0.008*** | 0.007** | -0.001 | 0.000 | 0.001 | 0.002 |
| value (log) | (0.003) | (0.002) | (0.002) | (0.003) | (0.005) | (0.004) | (0.004) | (0.005) |
| Gender of | -0.012 | -0.005 | 0.003 | 0.012 | -0.068 | -0.053 | -0.037 | -0.020 |
| Assets owner | (0.031) | (0.023) | (0.023) | (0.033) | (0.055) | (0.041) | (0.041) | (0.058) |
| Free medical | 0.013 | 0.012 | 0.011 | 0.010 | -0.090* | -0.089** | -0.088** | -0.088 |
| services | (0.030) | (0.022) | (0.023) | (0.032) | (0.054) | (0.040) | (0.040) | (0.057) |
| Health group | 0.066* | 0.044 | 0.020 | -0.006 | 0.034 | 0.043 | 0.053 | 0.064 |
| | (0.040) | (0.030) | (0.030) | (0.043) | (0.070) | (0.052) | (0.051) | (0.073) |
| Financial | 0.093*** | 0.095*** | 0.097*** | 0.099*** | 0.147*** | 0.156*** | 0.165*** | 0.175*** |
| group | (0.028) | (0.021) | (0.021) | (0.030) | (0.048) | (0.036) | (0.036) | (0.051) |
| Received loan | 0.085 | 0.077* | 0.068 | 0.059 | 0.170* | 0.154** | 0.137* | 0.118 |
| | (0.060) | (0.045) | (0.046) | (0.065) | (0.098) | (0.073) | (0.073) | (0.103) |
| Remittances | 0.090 | 0.078* | 0.064 | 0.049 | 0.103 | 0.154** | 0.209*** | 0.268** |
| | (0.057) | (0.043) | (0.043) | (0.061) | (0.099) | (0.073) | (0.073) | (0.104) |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The relationship between extreme weather events and total consumption as well as non-food consumption is homogeneously negative and significant in all quantiles. Similarly, the interaction terms between health indicators and extreme temperatures on non-food consumption were negative and significant in all quantiles except at the third quantile. On the contrary, the interaction terms of health and extreme temperature on total consumption were consistently positive and significant in all quantiles while interaction terms between rainfall measure and health were homogeneously insignificant at all quantiles.

**Table 4.11**: Quantile FE results on health, weather shocks and interactions on non-food

| | Non-food consumption quantile | | | | Non-food consumption quantile | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | 0.2 | 0.4 | 0.6 | 0.8 | 0.2 | 0.4 | 0.6 | 0.8 |
| HHs member hospitalized | | | | | 0.043 (0.060) | 0.071 (0.044) | 0.101** (0.045) | 0.133** (0.064) |
| Days of illness | -0.001 (0.001) | -0.001 (0.001) | 0.000 (0.001) | 0.001 (0.001) | | | | |
| Extreme rain | -0.144* (0.079) | -0.139** (0.058) | -0.134** (0.056) | -0.128 (0.079) | -0.125* (0.067) | -0.123*** (0.049) | -0.121** (0.050) | -0.118* (0.071) |
| Extreme temperature | -0.078 (0.097) | -0.106 (0.072) | -0.137** (0.069) | -0.170 (0.097) | -0.180** (0.084) | -0.174*** (0.062) | -0.167*** (0.063) | -0.160* (0.089) |
| Health shock# extreme rain | 0.002 (0.004) | 0.002 (0.003) | 0.002 (0.003) | 0.002 (0.004) | 0.064 (0.160) | 0.074 (0.119) | 0.085 (0.120) | 0.096 (0.171) |
| Health shock# extreme temp | -0.016** (0.007) | -0.011 ** (0.005) | -0.006 (0.005) | -0.001 (0.007) | -0.359 (0.289) | -0.292 (0.213) | -0.221 (0.215) | -0.144 (0.308) |
| Household size | -0.101*** (0.024) | -0.098*** (0.017) | -0.096*** (0.017) | -0.092*** (0.024) | -0.106*** (0.022) | -0.103*** (0.016 | -0.100*** (0.016) | -0.097*** (0.023) |
| Assets value (log) | 0.097*** (0.030) | 0.114 *** (0.022) | 0.132*** (0.021) | 0.152*** (0.030) | 0.094*** (0.028) | 0.112*** (0.021) | 0.131*** (0.021) | 0.152*** (0.030) |
| Livestock value (log) | -0.001 (0.005) | 0.000 (0.004) | 0.001 (0.004) | 0.002 (0.005) | -0.001 (0.005) | 0.000 (0.004) | 0.001 (0.004) | 0.001 (0.005) |
| Gender of assets_owner | -0.065 (0.058) | -0.051 (0.043) | -0.036 (0.041) | -0.020 (0.058) | -0.067 (0.056) | -0.051 (0.041) | -0.033 (0.041) | -0.013 (0.059) |
| Free medical services | -0.072 (0.058) | -0.079 * (0.043) | -0.086** (0.041) | -0.095 (0.058) | -0.094* (0.055) | -0.095** (0.040) | -0.095** (0.041) | -0.096* (0.058) |
| Health group | 0.033 (0.074) | 0.042 (0.054) | 0.052 (0.053) | 0.062 (0.074) | 0.036 (0.070) | 0.039 (0.052) | 0.042 (0.052) | 0.046 (0.075) |
| Financial group | 0.153*** (0.051) | 0.160 *** (0.038) | 0.168*** (0.037) | 0.177*** (0.051) | 0.137*** (0.049) | 0.150*** (0.036) | 0.164*** (0.036) | 0.179*** (0.052) |
| Received loan | 0.175** (0.105) | 0.158 ** (0.077) | 0.139 (0.075) | 0.119 (0.105) | 0.172* (0.100) | 0.153** (0.074) | 0.132** (0.074) | 0.110 (0.106) |
| Remittances | 0.099 (0.105) | 0.153** (0.077) | 0.210*** (0.075) | 0.273*** (0.105) | 0.105 (0.100) | 0.153** (0.074) | 0.205*** (0.075) | 0.260** (0.107) |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11 presents quantile regression results of our main covariates on non-food consumption. Hospitalization was positively and significantly associated with non-food consumption, only for the top quantiles. The effect remained insignificant at the 1st and 2nd quantile. Effect of extreme rain was homogeneously negative and significant at all quantiles, as well as for temperature when hospitalized health measure is used. Even though the interaction term between temperature and days of illness on non-food consumption is observed, the effect was only significant at the lower quantiles. In summary, quantiles regression estimate show that households at the top quantiles increased non-food consumption due to hospitalization while households at the bottom quantiles experiencing both health shocks and extreme temperature reduced non-food consumption significantly.

**IV fixed effect regression of health on consumption**

**Table 4.12**: IV FE results of days of illness and weather shocks on consumption

| Variables | Total consumption | | Food consumption | | Non- food consumption | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HHs member sick more than 30 days | -1.263* | | -1.146 | | -3.268** | |
| | (0.738) | | (0.718) | | (1.515) | |
| Days of illness | | -0.022* | | -0.024** | | -0.039** |
| | | (0.011) | | (0.012) | | (0.019) |
| Extreme rain | -0.127*** | -0.113*** | -0.125*** | -0.109*** | -0.097 | -0.075 |
| | (0.035) | (0.036) | (0.034) | (0.037) | (0.071) | (0.062) |
| Extreme temperature | -0.080 | -0.116*** | -0.048 | -0.078* | -0.066 | -0.171** |
| | (0.052) | (0.044) | (0.051) | (0.046) | (0.107) | (0.075) |
| Household size | -0.101*** | -0.100*** | -0.114*** | -0.110*** | -0.048 | -0.063** |
| | (0.017) | (0.016) | (0.016) | (0.017) | (0.034) | (0.027) |
| Assets value (log) | 0.104*** | 0.109*** | 0.073*** | 0.082*** | 0.165*** | 0.161*** |
| | (0.017) | (0.018) | (0.017) | (0.019) | (0.036) | (0.031) |
| Livestock value (log) | 0.008*** | 0.007** | 0.011*** | 0.010*** | -0.000 | -0.002 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.006) | (0.005) |
| Gender of assets_owner | -0.008 | 0.009 | -0.003 | 0.014 | -0.066 | -0.029 |
| | (0.029) | (0.029) | (0.029) | (0.030) | (0.060) | (0.050) |
| Free medical services | 0.070 | 0.195** | 0.105** | 0.251** | 0.057 | 0.230 |
| | (0.044) | (0.098) | (0.042) | (0.101) | (0.090) | (0.167) |
| Health_related_group | 0.054 | 0.028 | 0.051 | 0.027 | 0.109 | 0.043 |
| | (0.039) | (0.037) | (0.038) | (0.039) | (0.081) | (0.063) |
| Financial_related_group | 0.098*** | 0.100*** | 0.071*** | 0.073*** | 0.159*** | 0.162*** |
| | (0.026) | (0.027) | (0.026) | (0.028) | (0.054) | (0.045) |
| Received loan | 0.087 | 0.143** | 0.073 | 0.137** | 0.189 | 0.273** |
| | (0.056) | (0.067) | (0.055) | (0.069) | (0.115) | (0.114) |
| Remittances | 0.069 | 0.047 | -0.001 | -0.025 | 0.189* | 0.150* |
| | (0.051) | (0.052) | (0.049) | (0.054) | (0.104) | (0.089) |
| Observations | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 |
| Number of HHID | 621 | 621 | 621 | 621 | 621 | 621 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

As earlier discussed, health can be non-random with simultaneity and selection bias therefore endogenous. We present results of the instrumental fixed effects regressions where health is instrumented with temperature in the two months before the interview and its quadratic term. Results for the second stage estimations in Table 4.12 indicate that weather induced health shocks in terms of days of illness, had significant and negative effects on total consumption and non-food consumption. The results were significant for food consumption, only when continuous health shock measure is used. The effect sizes were higher for non-food consumption, where households with at least one-member sick for more than 30 days reduced consumption by at least 300%. An increase in one day of illness, reduced total consumption by 2.2%, food consumption by 2.4% and non-food consumption by 4%. Extreme rain reduced food consumption and total consumption, while the effect was insignificant for non-food consumption. Extreme temperature reduced all consumption categories but only for regressions with days of illness. We do not report instrumental variable results for effect of hospitalization on consumption because the instruments were not significantly correlated with the endogenous variable.

**Potential pathways**

The possible mechanisms through which illness can affect consumption is through out-of-pocket health expenditures, income and labour supply or labour productivity. Sick individuals or caregivers may incur costs related to medical care or transactions costs such as transport during illness events. Furthermore, they might reduce work time in the course of seeking medical attention or when accompanying their family members during doctor visits, and sick individuals may take longer or unable to perform usual tasks, therefore leading to reduced labour productivity and reduced income.

We report panel Tobit results for medical expenditures and wage labour income due to the presence of many zeros and fixed effects for agricultural labour supply. Results in Table 4.13, columns 1-3 shows the effect of illness on household health expenditures. As anticipated, there was significant and positive effects of all measures of illness on health expenditures. A larger effect is observed for illness variables where a household member was sick for more than 30 days and hospitalization. In particular, a household with members sick more than 30 days increased medical expenditures by approximately 169, 000 UGX while hospitalization increased medical expenditures by 149,600 UGX. These figures are relatively smaller given that user fees in government health centres where most rural households visit are relatively lower. In fact, most sick households reported to have received free medical services as shown in Figure 4.7. This is consistent with empirical results in Table 4.13 where free medical services reduced household medical expenditures by up to 44, 920 UGX. Extremely high rainfall was also associated with increased medical expenditures while the effect of temperature was negative.

We do not find any significant changes of illness on wage labour earnings while the effect of illness on family labour is weakly significant, for illnesses that lasted more than 30 days.

**Table 4.13**: Effect of illness and weather on health costs, wage income and family labour

| Variables | Health expenditures (0000 UGX) | | | Labour income (0000 UGX) | | | Family Agric labour (person days) | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| HHs member sick > 30 days | 16.899*** | | | -4.273 | | | -6.419* | | |
| | (1.011) | | | (5.426) | | | (3.387) | | |
| Days of illness | | 0.430*** | | | 0.052 | | | -0.053 | |
| | | (0.017) | | | (0.090) | | | (0.058) | |
| Hospitalized | | | 14.961*** | | | 2.935 | | | 2.711 |
| | | | (0.795) | | | (4.301) | | | (2.651) |
| Extreme rain | 2.789*** | 1.965* | 2.543*** | 7.371* | 8.023 | 5.464 | -3.928 | -3.569 | -3.026 |
| | (0.892) | (1.042) | (0.911) | (4.395) | (5.231) | (4.528) | (2.874) | (3.376) | (2.936) |
| Extreme temperature | -6.144*** | -6.125*** | -4.663*** | -31.899*** | -34.981*** | -29.521*** | -7.599** | -6.925* | -7.296** |
| | (1.289) | (1.413) | (1.274) | (6.129) | (6.738) | (6.097) | (3.598) | (3.896) | (3.619) |
| Sick 30days# extreme rain | -1.372 | | | -10.938 | | | 5.035 | | |
| | (2.620) | | | (14.359) | | | (8.751) | | |
| Sick 30days# extreme temp | 10.129*** | | | 23.989 | | | -1.563 | | |
| | (3.390) | | | (18.357) | | | (10.709) | | |
| Days of illness# extreme rain | | 0.027 | | | -0.118 | | | 0.003 | |
| | | (0.044) | | | (0.239) | | | (0.151) | |
| Days of illness # extreme temp | | 0.206*** | | | 0.555 | | | -0.114 | |
| | | (0.063) | | | (0.338) | | | (0.199) | |
| Hospitalized# extreme rain | | | 0.107 | | | 8.018 | | | -4.327 |
| | | | (1.969) | | | (10.463) | | | (6.656) |
| Hospitalized #extreme temp | | | 13.384*** | | | -3.059 | | | -4.546 |
| | | | (3.339) | | | (19.832) | | | (10.715) |
| Household size | 0.589*** | 0.198 | 0.568*** | 2.535*** | 2.425*** | 2.493*** | 3.236*** | 3.236*** | 3.094*** |
| | (0.157) | (0.143) | (0.154) | (0.799) | (0.804) | (0.800) | (0.947) | (0.949) | (0.947) |
| Assets value (log) | 2.496*** | 1.987*** | 2.482*** | 12.139*** | 11.951*** | 12.031*** | 1.462 | 1.449 | 1.336 |
| | (0.275) | (0.255) | (0.271) | (1.404) | (1.412) | (1.405) | (1.168) | (1.169) | (1.169) |
| Livestock value (log) | -0.055 | -0.035 | -0.006 | 0.292 | 0.286 | 0.302 | -0.158 | -0.159 | -0.157 |
| | (0.068) | (0.064) | (0.067) | (0.334) | (0.334) | (0.334) | (0.222) | (0.222) | (0.222) |
| Gender of assets_owner | -1.220* | -1.456** | -0.901 | -8.032** | -8.156** | -8.091** | 3.176 | 3.265 | 3.328 |
| | (0.669) | (0.632) | (0.661) | (3.348) | (3.351) | (3.350) | (2.356) | (2.357) | (2.359) |
| Free medical services | -1.591** | -4.492*** | -1.370* | -4.873 | -5.882 | -5.127 | 2.760 | 3.024 | 2.369 |
| | (0.731) | (0.713) | (0.722) | (3.626) | (3.694) | (3.623) | (2.251) | (2.296) | (2.251) |
| Observations | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Extreme temperature decreased labour income as well as well as family labour supply to agricultural activities.

The null effect of illness on labour income could be explained as follows, most rural households are engaged in informal on-farm employment, therefore, in case of any sickness, households with sick individuals may negotiate with the employer so that other households' members may step in to cover up for respective activities and earn income. Therefore, household income remains unchanged. With regards to family labour, rural households use different labour coping strategies in case of sickness, in order to compensate for lost labour.

**Consumption smoothing mechanisms, healthcare and labour coping strategies**

So far, we have reported that illness when treated as an exogeneous variable did not have an effect on total consumption and food consumption while the effect was mixed on non-food consumption. However, negative significant effects of health on consumption are only observed when health is interacted with extreme temperature and when health is treated as an endogenous variable and instrumented with weather measures. These mixed findings, partly provides evidence of the ability of households to insure economic costs arising from illness, to some extent.

In general, results in consumption models (Tables 4.8-4.12) indicate that belonging to financial related groups was positively associated with all consumption categories. The effect was homogeneously significant in all consumption quantiles. On the other hand, participation in health or wellbeing group only increased total consumption of households in the bottom quantile as shown in Table 4.10. The observed increase in total consumption is mostly driven by food consumption, where participation in both health-related group and financial group increased food consumption[29] at the lower quantile. Access to loans significantly increased total and non-food consumption at the bottom and middle quantile households and not at the top quantile. However, remittances increased total and non-food consumption at the middle and top quintile but not at the bottom quantile. For the whole sample, we do not find any significant effect of loans and remittances on food consumption.

Households assets and livestock value was positively and significantly associated with consumption, including food consumption while livestock value did not have an effect on non-food consumption. We find that access to free medical services reduced health care expenditures significantly and increased food consumption, while the effect was negative on non-food consumption. In fact, the effect was positive and significant for the bottom and middle quantiles but not the top quantile. Other major coping mechanisms for health care expenditures include; households' savings, used by 27% of the total households and 38% of households who were sick,

[29] Results are not presented here, but are available on request.

sales of agricultural produce, livestock sales and borrowing or assistance from friends as shown in Figure 4.7.

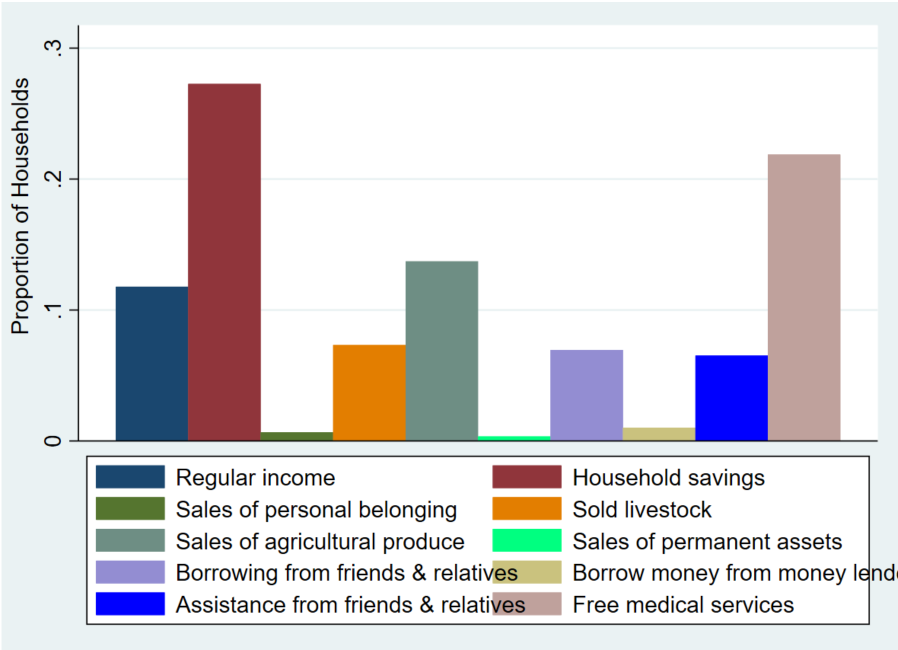


**Figure 4.7**: Households using different financial sources for medical expenditures

We did not find significant effect of illness on labour supply and earned income. These findings indicate that households used different labour related coping strategies to safeguard household income from losses related to illnesses. Unfortunately, data on labour coping strategies was only collected in wave 6 where households indicated the strategies they used to compensate for lost labour if a family member was unable perform usual activities due to illness or injury. Therefore, we only present descriptive statistics of the different labour coping strategies that households use since we also anticipate that these strategies may not change overtime.

Results in Figure 4.8 reveal that over a third of households hired labour, reallocated tasks from ill members to healthy members and increased labour hours of healthy members. Only a small proportion used free community labour.

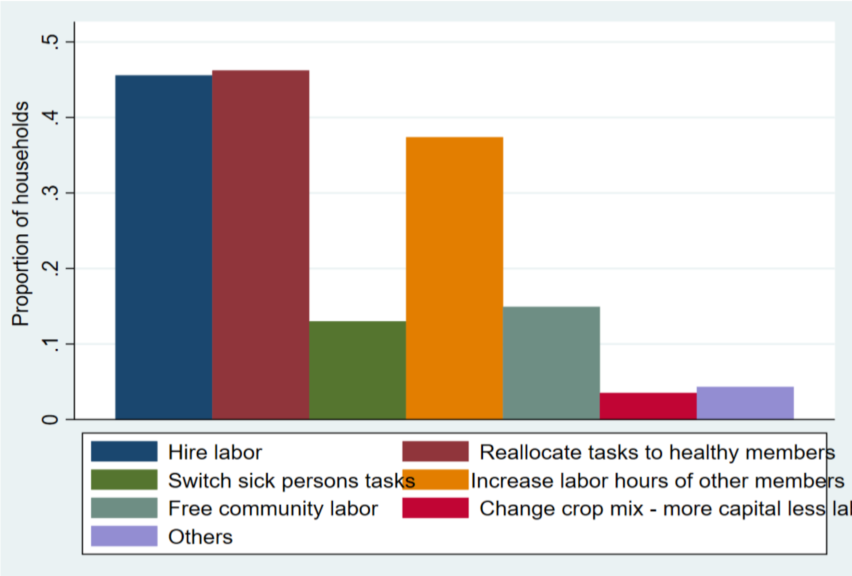


**Figure 4.8**: Proportion of households using different labour adjustment strategies

### 4.4.1 Association between food consumption and health

Table 4.14 presents estimates from the PPMLHDFE model on the effect of food consumption on health as measured by days of illness. Apart from by per capita food expenditure, we explore other food related measures such as household diet diversity, diversity in animal source food (ASF) and share of vegetables and fruits expenditure out of the total food expenditure. Columns 1, 4, 7 and 10 presents coefficients of food and weather shocks without controlling for seasonal effects. While increased food expenditure was significantly associated with poor household health, increased consumption of ASF led to better health. Similarly, increased HDDS and share of fruits and vegetables were associated with reduced days of illness, even though the effect was insignificant. Similar results are observed after controlling for wave effects as shown in columns, 2, 5, 8 and 11, even though the effect sizes and significance levels reduced. After inclusion of the interaction terms between food consumption and weather, the main effects were significant only for food expenditure and food budget share on fruits and vegetables with positive and negative effects on days of illness respectively.

Households exposure to heavy rainfall led to increased days of illness while high temperature had an opposite effect. However, the effect of weather extremes on illness was only significant in most estimation excluding wave effects. Even though extreme rainfall in the previous wave was associated with poor health, the effect was insignificant, except in estimations consisting of ASF in column 9 where lagged extreme rainfall significantly increased days of illness. Furthermore, the interaction effect was negative and significant, implying that households that experienced high rainfall but consumed diverse animal products had better health. In other words, consumption of diverse animal products negated the adverse effects of high rainfall on health. These results suggest that the quality of foods consumed matter for better health.

Table 4.14: Effect of food consumption on household health (*Days of illness*)

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L1. Food expenditure | 0.135*** | 0.077* | 0.098** | | | | | | | | | |
| | (0.045) | (0.046) | (0.049) | | | | | | | | | |
| L1. HDDS | | | | -0.020 | -0.017 | -0.018 | | | | | | |
| | | | | (0.014) | (0.014) | (0.015) | | | | | | |
| L1. Animal source food count | | | | | | | -0.058** | -0.044* | -0.038 | | | |
| | | | | | | | (0.024) | (0.023) | (0.026) | | | |
| L1. Share of fruits and vegetables | | | | | | | | | | -0.334 | -0.333 | -0.522** |
| | | | | | | | | | | (0.232) | (0.236) | (0.255) |
| Extreme rain | 0.153*** | 0.017 | 0.078 | 0.160*** | 0.013 | 0.070 | 0.162*** | 0.015 | 0.080 | 0.159*** | 0.016 | 0.088 |
| | (0.058) | (0.064) | (0.075) | (0.058) | (0.064) | (0.075) | (0.058) | (0.064) | (0.075) | (0.058) | (0.064) | (0.075) |
| Extreme temperature | -0.393*** | -0.138 | -0.033 | -0.410*** | -0.136 | -0.028 | -0.405*** | -0.134 | -0.022 | -0.404*** | -0.137 | -0.022 |
| | (0.096) | (0.104) | (0.103) | (0.096) | (0.105) | (0.103) | (0.097) | (0.105) | (0.102) | (0.096) | (0.104) | (0.101) |
| L1. Extreme rain | | | 0.417 | | | 0.248 | | | 0.190** | | | 0.004 |
| | | | (0.952) | | | (0.225) | | | (0.085) | | | (0.102) |
| L1. Extreme temperature | | | 1.970 | | | -0.323 | | | -0.660*** | | | -0.783*** |
| | | | (1.777) | | | (0.399) | | | (0.180) | | | (0.238) |
| L1. Extreme rain#food expenditure | | | -0.027 | | | | | | | | | |
| | | | (0.084) | | | | | | | | | |
| L1. Extreme temperature#food expend | | | -0.254 | | | | | | | | | |
| | | | (0.171) | | | | | | | | | |
| L1. Extreme rain# HDDS | | | | | | -0.019 | | | | | | |
| | | | | | | (0.029) | | | | | | |
| L1. Extreme temperature#HDDS | | | | | | -0.067 | | | | | | |
| | | | | | | (0.067) | | | | | | |
| L1. Extreme rain#ASF | | | | | | | | | -0.088* | | | |
| | | | | | | | | | (0.050) | | | |
| L1. Extreme temperature#ASF | | | | | | | | | -0.077 | | | |
| | | | | | | | | | (0.134) | | | |
| L1. Extreme rain#fruits & vegetables | | | | | | | | | | | | 0.860 |
| | | | | | | | | | | | | (0.612) |
| L1. extreme temperature# fruits & veges | | | | | | | | | | | | 0.596 |
| | | | | | | | | | | | | (1.374) |
| Other covariates | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave covariates | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Observations | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## 4.5 Discussions and conclusions

Using different health indicators and panel regression methods, most of our results indicate that food consumption was unaffected by illness, implying that households were able to fully insure food consumption against illness. Uganda is one of the countries that produces sufficient food for its population, food prices are lower and food availability is not a major challenge, given that a substantial population is food secure and can afford a diversified diet with three meals per day (Food and Agriculture Organization of the United Nations, 2020b). Therefore, despite increased cost of illness in case of a health shock, most households would still consume enough food from saved produce or depend on informal transfers from friends and relatives both in terms of cash and kind thus mitigating consumption fluctuations.

However, we find that food consumption was negatively affected by extreme weather events. This is expected, given that households that are chronically food-insecure in Uganda are located in areas experiencing weather shocks. Floods may therefore have an effect on food consumption both through reduced productivity or loss of crop land as well as disrupting food channels due to damaged road infrastructure limiting access of food to food insufficient households. These results are consistent with Kurosaki (2015) who found a negative effect of floods on consumption in Pakistan and Oskorouchi and Sousa-Poza (2021) who find decreased calorie consumption due to flood events. Our results support the argument that covariates shocks are not perfectly insured. Furthermore, given an increase in flood events across East Africa (even in areas that did not historically experience floods or extreme wetness), some households might not have established effective risk sharing institutions to mitigate the negative effects of this new shock (floods) on consumption, thus not resilient to this climatic shock. Inability of households to bounce back in a timely way when faced with hazards has adverse effects not only on consumption but also on other development outcomes.

On non-food consumption, we find mixed effects of illness depending on the health measure used. For instance, hospitalization increased non-food consumption while households with at least one-member sick for more than 30 days reduced their non-food consumption. However, the latter variable was only significant when instrumented with an alternative temperature measure. We also find that interaction terms between sick days or days of illness and extreme temperature on non-food consumption are negative and significant. Quantiles regression showed heterogeneity in the above effects where households at the top quantiles increased non-food consumption due to hospitalization while households at the bottom quantiles experiencing both health shocks and extreme temperature reduced non-food consumption significantly. Hospitalization results are consistent with Wagstaff (2007) who found increased non-food expenditures such as electricity and housing due to hospitalization. He argued that hospitalized members need comfortable conditions while recovering from home after being discharged, thus households might reallocate resources to cater for sick person's needs based on health staff recommendations. Indeed, only rural households with substantial resources or those that can access credit can manage to provide intensive care and suitable recovery conditions for their sick individuals at home upon hospital discharge.

Further results on income, labour and medical expenditures revealed that wage labour income and person days of family farm labour were unaffected by illness. While this finding is in contrast with Lenhart (2019) and Hangoma et al. (2018), it's rather partly consistent with Wagstaff (2007) who found that most of the health shocks, apart from death were not statistically significant. Furthermore, Gertler and Gruber (2002) found out illness as measured by symptoms did not affect labour in terms of hours worked. This implied that households used different labour coping strategies in the event of illness. In Ugandan context, majority of households hired labour, reallocated tasks of ill members among health members and increased working hours of the non-sick individuals. Our findings on illness increasing health expenditures is consistent with Gertler and Gruber (2002) and Wagstaff (2007) on hospitalization.

We found a positive effect of increased food expenditure on days of illness. However, diverse and better-quality foods in terms of ASF and consumption of fruits and vegetables were associated with better health. In general, food expenditure results are partly consistent with Tumin et al. (2012) who despite reporting a positive relationship between a large food budget and better health, they found that increased spending on food produced and eaten at home were associated with poor health. The positive effect of food expenditures on better health was mostly driven by away from home food expenditures. In our study we focused only on rural households whose food consumption is mostly from home produce as opposed to dining out. Similarly, Alston et al. (2009) reported that although food stamp programs (FSP) in the USA increased food expenditures among households with low income status, majority of studies found that participants in FSP, especially women were more likely to be obese and overweight which are risk factors for poor health that non-participants. Alston et al. (2009) further argued that, the program would be beneficial if it was redesigned to specify particular healthy foods to be included in the program, especially meat and low-dairy products, fruits and vegetables, legumes and dried beans, whole grains which are associated with low mortality and illness (Kant, 2004) opposed to beverages and energy dense foods. Indeed, we found that increased diversity of ASF and increased share of fruits and vegetables was associated with better household health.

Our findings have the following policy implications, since the main cost of illness in Uganda is in terms of health expenditures and not necessarily lost wage earnings, interventions that reduce out-of-pocket expenditures and minimize financial risks such as national health insurance scheme that enhance universal health coverage are recommended. Secondly, flood protection and risk reduction strategies such as floods early warning systems will help mitigate adverse effects of floods on consumption, and illness. Finally, social protection measures such as access to credit, social networks, remittances and both formal and informal safety nets are crucial for consumption in the face of the changing climate. The aforementioned measures are recommended for strengthening food systems resilience and overall household resilience against shocks.

# Chapter 5: General conclusion and policy implications

This dissertation sought to establish the effects of weather variability on health outcomes of vulnerable members in households, as well as assess the economic implications of both weather and health shocks on rural households in Uganda. Using high resolution weather data and national representative low-frequency and high frequency panel survey datasets, empirical studies in this dissertation provide evidence of the adverse effects of weather variability on health-related outcomes. Furthermore, possible recommendations that might inform and guide policy makers in developing countries are highlighted.

## 5.1 Summary of key findings

Chapter 2, guided by a child health production function framework estimated the effect of extreme weather events on child health. Using LSMS data (2009 -2014) and two-step econometric approaches, the study unpacked the causal mechanisms through which extreme weather events affects health. Results of the first stage 2SLS on HAZ regressions showed that extreme weather events were significantly associated with lower crop productivity and limited availability of macronutrients and micronutrients in previous year. Fairly larger effects occurred through droughts on crop production (a reduction of 73%) and calories (a reduction of 59%) as opposed to micronutrients (29% reduction in zinc supply). In fact, vitamin A dense food crops were tolerant to short term drought, but significantly affected by an increase in frequency of drought and heat wave events. Similar results were reported for WAZ and WHZ regressions estimates, where droughts reduced crop productivity, calories, protein, and zinc supply by 84%, 51%, 19% and 12% respectively. In the second stage, micronutrients especially zinc had a larger effect on child HAZ, WAZ and WHZ as opposed to the effect of macronutrients and crop yield on child health. A 10% increase in zinc and protein increased child HAZ by 0.056 and 0.037standard deviations respectively. Heterogenous effects of nutrients on child HAZ, WAZ and WHZ were observed among boys and girls. While both boys and girls WAZ and WHZ were sensitive to nutrients availability, only boys HAZ were significantly affected by nutrient adequacies. The magnitude of effect of nutrients on WHZ was higher in girls.

Further findings on other pathways indicate that extreme weather events reduced crop market participation. However, market participation did not translate to better child health. Only cumulative extreme weather events affected livestock holdings as opposed to a one-time seasonal drought while an increase in livestock holdings was associated with better child nutritional scores, especially WAZ and WHZ. Extreme weather events also increased the likelihood of child diseases such as diarrhoea and fever. For instance, heatwaves increased both the probability of diarrhoea and fever by about 2-3 percentage points, and in some instances dry spells were also positively associated with diarrhoea. Similarly, diarrhoea significantly reduced child undernutrition measures.

Chapter 3 focussed on the gender dimensions of weather variability on illness of rural individuals using LSMS data (2009 – 2014). In particular, the study assessed the total effect of weather variability on illness at both the extensive and intensive margins, and the overall effect among men and women of the working age. Furthermore, the indirect effect occurring through the water collection access pathway was established and the gender gap in health that would be eliminated if both gender groups had similar resources or characteristics was quantified. Findings showed than women were more ill than men, and there were significant gender differences in covariates, especially in health seeking behaviours. Lower rainfall than the long-term mean increased the probability of illness and workdays lost as well as days of illness in both men and women, with a higher effect in women. Similar effect was observed on temperature variables where an increase in temperature was associated with increased illness in both groups. Moreover, the study found that the relationship between low rainfall /increased temperature at the extensive margin of illness was fully mediated by water collection time burden among women, while the mediation process was partial in men. This implies that the stated weather variables significantly increased water collection time in women, and in turn the increased water collection time significantly increased illness in women.

Other determinants of illness include age, education, wealth index, income, occupation, use of treated mosquito nets and health care services such as different health care facilities where men and women visited while sick, and distance to these facilities. Decomposition results revealed that a substantial gender health gap (25-57%) in terms of illness and workday lost would be narrowed down if gender discrimination and biases in access to resources, especially health care services would be addressed. Differences in education, age, marital status, occupation and income also explained substantial proportion of the women-men illness gap.

The last empirical chapter 4, deviated from the other studies by utilizing a more recent innovative intra-annual high frequency panel primary dataset collected after every two to three months, to address the short-run connections between health and weather shocks and consumption at household level. In rural agricultural households, floods and droughts are key drivers of adverse seasonality and its often argued that seasonal variations matter for food availability, employment as well as for spread of diseases. Therefore, the above outcomes are negatively affected in the absence of effective coping strategies and risk sharing institutions, further increasing the vulnerability of households falling into poverty.

Findings on our primary outcomes revealed that households spent 69% of the total consumption expenditure on food items. Moreover, there was substantial consumption mobility overtime and poverty was transitory rather than chronic. Only 4% of households were consistently in the bottom quintiles in all the survey rounds. However, the transition matrix between two time periods revealed that approximately 60-75% of households who were in the bottom quintile in wave 4 remained poor in wave 5 which was a lean season and a substantial proportion of households previously in middle quintiles became poor during lean season. This indicates the vulnerability of households falling into poverty during lean seasons. Important household characteristics, livelihoods and shocks categorizing different households based on poverty transition status include; household size, livestock value, group participation, wage income, diet diversity, weather shocks and health shocks in a few instances.

Empirical results showed that in the short run, food and total consumption remained unaffected by illness. Furthermore, illness did not significantly affect the household dietary diversity. On the contrary, food, non-food and total consumption were negatively affected by both rainfall and temperature extremes. Extreme high rainfall reduced consumption by 11-15% while extreme temperatures reduced consumption by 10-20%. These results imply that covariates shocks were not perfectly insured while food consumption was insured against idiosyncratic shocks. Further results revealed that extreme weather events intensified the negative effect of health shocks on illness since the interaction terms between temperature extremes and days of illness on non-food consumption were negative. Non-food consumption of households in the bottom quantiles were adversely affected by the interaction of health shocks and extreme temperature as compared to those at the top quantiles. In fact, households at the top quantile increased non-food consumption due to hospitalization. On pathways, we find that illness and extreme rainfall significantly increased health expenditures, especially in households with a hospitalized member or with a member sick more than 30 days. However, wage labour income and family farm labour were unaffected with illness, despite being affected by extreme temperature. These mixed findings, provides evidence of the ability of households to insure economic costs arising from illness, to some extent.

Results on the association between food consumption and health revealed that the quality of food consumed matters a lot for better health as opposed to the quantity of food consumed. For instance, while increased food expenditure was significantly associated with poor household health, increased consumption of ASF and share of fruits and vegetables were associated with reduced days of illness, even though the effect for ASF was only significant in estimations without interactions, while the main effect of fruits and vegetables was significant only in the interaction model. Exposure to heavy rainfall led to poor household health, with significant effects in models excluding seasonal effects and interactions. However, a significant and positive effect of lagged extreme rain on days of illness and a negative effect of the interactions between lagged rainfall and ASF was reported. This implies that even though extreme rainfall led to poor household health, increased consumption of diverse ASF helped mitigate the negative effects of rainfall on health.

Finally, the COVID-19 pandemic is also a threat to household food security, health and welfare. We found that total and non-food consumption were low in wave 1 and wave 6 as compared to other waves and this could partly be attributed to the two COVID-19 lockdown measures implemented just before the first and sixth survey rounds. However, it seems lockdown measures did not substantially affect availability of major food staples, vegetables and fruits local markets and access to medical services in rural areas. Less than 10% of the rural households were affected by COVID lockdown in terms of access to medical services, with most of the affected households residing in districts that had registered some COVID-19 cases. Specifically, majority of the affected households were sick and unable to access health care and some delayed or were unable to complete any scheduled health visits due to lockdown, mainly because of unavailability and unaffordability of transport means.

## 5.2 Policy recommendations

Findings reported in the three empirical chapters covered in this dissertation have important policy implications for development in Uganda and other lower- and middle-income countries vulnerable to extreme weather events. The results from the second chapter provided evidence of the interlinkages between extreme weather events, nutrient availability/disease and child health. We showed that extreme weather events affect not only the quantity of production but also quality of production which is crucial for human health. In addition, the study identified different adaptation strategies effective in minimizing health effects resulting from extreme weather events either directly or indirectly. These strategies include precautionary savings, government aid, non-farm work, sale of assets and credit access which were positively associated with better child health scores while crop diversification, improved seed, pesticide use, fertilizers, water harvesting and market access led to increased nutrient availability and yield. Investment in these good agronomic practices and other ex-ante or anticipatory coping measures that improve crop productivity, nutrition, livelihoods and protect households from climate related health risks are key recommendations for policy makers.

Rural financial institutions that promote savings and credit access, especially micro-finance institutions and Village Savings and Loan Associations (VSLAs) should also be strengthened to allow the affected households to meet their food and nutrient requirements instead of reverting to strategies such as involuntary change of diet that are harmful to their health. Furthermore, rural households should be equipped with knowledge on good WASH strategies. Local and national governments should improve road infrastructure to facilitate free movement of goods, people, access to markets even during flooding periods. This is essential in reducing transaction costs associated with movement and hedging rural households against price hikes, consequently reducing the disease burden associated with food, water, nutritional deficiencies and road accidents.

Findings from the third chapter revealed that low cost technologies such as domestic rain water harvesting can help increase water quantities for better hygiene practises as well as reduce water collection time. Such strategies facilitate more engagement of women in economic activities as well as limit the disease burden resulting from walking longer distances, violence and other water and sanitation related diseases. With proper education, use of irrigation which is crucial for agricultural productivity can also be leveraged in order to enhance water quantities for domestic use and improve health for individuals. Equity in health care access especially among women and men should also be advocated for, in order to reduce the observed health inequalities. This can be achieved through strategies that promote universal health coverage such as national health insurance and community-based insurance schemes, which are not only instrumental for better health but will also reduce the burden associated with out-of-pocket expenditures, minimize financial risks and improve overall welfare of households in Uganda. Indeed, results in our fourth chapter pointed out that the main cost of illness in Uganda was health expenditures.

Other policy recommendations emanating from the fourth chapter include social protection measures related to labour market and social assistance such as formal and informal safety nets, remittances and credit access are of importance in ensuring food security and poverty reduction. Food assistance programs should distribute and promote consumption of healthy diets, rather than energy dense foods so as to help reduce the disease burden among households in Uganda. Furthermore, households should leverage on different risk-pooling institutions such as social networks in order to access relevant information on health care, weather changes as well as ease liquidity constrains when faced with shocks. Finally, policy makers can utilize these networks in disseminating relevant knowledge on flood protection and risk reduction strategies such as early warning systems and weather index-based crop and livestock insurance in order to enhance adaptation of these strategies, consequently smoothing consumption and minimizing health risks.

In summary, all the three empirical chapters highlights important measures that could be used to not only adapt but also increase individual and household resilience against different types of shocks. These measures could either lower exposure to risk, reduce vulnerabilities and hazards, and categorized in one or several core elements of resilience, namely; adaptive, absorptive and transformative capacities. Actions such as social networks and collective actions can be used by households to prepare, adapt and recover from shocks. Therefore, policies makers should advocate for measures that not only addresses the adaptive capacity but also absorptive and transformative capacities so as to successfully deal with risks and uncertainties, and future shocks given that "resilience is a forward-looking notion".

## 5.3 Limitations and suggestion for future research

Limitations of respective empirical studies relate to the datasets used for empirical analysis. While LSMS was more robust and provided data on a range of variables, the study used only a five-year dataset given that GPS data on the subsequent waves were not provided. Furthermore, anthropometric data were only collected for children less than five years in each wave, suggesting that health data of children who were five years old in the first wave was not collected in the second wave. This limited studying long-term impacts of extreme weather events of children health and other human capital development outcomes such as education and employment. There was also a sample refresh in 2013 wave causing attrition of individuals and households. Future studies should consider more long-term socio-economic panels and up-to date data in the analysis, and further experimental analysis.

Moreover, the studies focused on effects of weather variability on health and did not project future health impacts of climate events under different climate change scenarios. This is an interesting research area for future studies. Other limitations relate to missing data on very important covariates such as breastfeeding, complementary feeding of all children, mother health endowment, households' access to nutritional information, health insurance and health behaviours and health adaptations. In the second empirical chapter, health data available were self-reported and only for the last 30 days before the interview and based on symptoms rather than diseases. Additional data with a wider recall period such as 6-12 months would have been collected to perfectly match with our weather indicators. Furthermore, clinical data would have complemented the self-reported health measures, and ideal as a true measure of health. Despite using a long-term weather dataset, weather data were for the enumeration areas and household as opposed to the specific places where men and women spent time.

In chapter 4, the pathways through which extreme weather events influence health, especially the agricultural production component was not explored. Furthermore, data was collected during COVID-19 period and possibility of some results to be driven by some of the lockdown measures. Therefore, even though the cases in the country of study were lower, these results should be interpreted with caution and further studies should be conducted in absence of COVID-19. Alternatively, future studies could leverage on our study to explore development outcomes during and after COVID-19.

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# Appendix

**Table 7.1**: Summary statistics of children aged 7 -59 months, socio-economics and weather.

| Variable | Variable definition | Mean | SD |
|---|---|---|---|
| ***Children outcome variables*** | | | |
| HAZ | Height for age Z scores of children aged 7-59 months | -1.13 | (1.42) |
| WAZ | Weight for age Z scores of children aged 7-59 months | -1.02 | (1.32) |
| WHZ | Weight for height Z scores of children aged 7-59 months | -0.25 | (1.18) |
| Stunting [30] | A dummy variable if child height for age z scores is less than 2 SD | 0.27 | (0.44) |
| Underweight | A dummy variable if child weight for age z scores is less than 2 SD | 0.21 | (0.41) |
| Wasting | A dummy variable if child weight for height z scores is less than 2 SD | 0.07 | (0.25) |
| ***Pathway variables*** | | | |
| Child fever | A dummy variable (1=Yes) if a child had last month fever and 0 otherwise | 0.30 | (0.46) |
| Child diarrhoea | A dummy variable (1=Yes) if a child had diarrhoea last and 0 otherwise | 0.09 | (0.28) |
| Log of crop yield | Logarithm value of crop productivity in kg per acre in the first season | 6.25 | (2.10) |
| Sold crop | A dummy crop if a household sold any crop in either season | 0.86 | (0.35) |
| TLU[31] | Tropical Livestock Units (a weighted livestock numbers- converted to a common unit) | 2.31 | (6.70) |
| Road access | A dummy variable of households whose road was inaccessible due to bad weather | 0.137 | (0.34) |
| ***Other child characteristics*** | | | |
| Sex of child | A dummy variable, 1 if child is male and 0 if female | 0.50 | (0.50) |
| Age of child | Child age in complete months | 32.4 | (15.04) |
| Age of child squared | The square of the child age in months | 1273 | (988) |
| Quarter of birth ($1^{st}$) | If child was born in January, February and March | 0.22 | (0.42) |
| Quarter of birth ($2^{nd}$) | If child was born in April, May and June | 0.25 | (0.43) |
| Quarter of birth ($3^{rd}$) | If child was born in July, August, September | 0.23 | (0.42) |
| Quarter of birth ($4^{th}$) | If child was born in October, November, December | 0.24 | (0.43) |
| Mosquito net | A dummy variable if children slept under treated mosquito net | 0.48 | (0.50) |
| ***Household variables including coping strategies*** | | | |
| Sex of HHs head | A dummy variable, 1 if household head is male and 0 if female | 0.80 | (0.40) |
| Age of the Head | Household head age in complete years | 41.3 | (12.99) |
| Household head education | Number of education years of the household head | 5.61 | (3.69) |
| Dependency ratio | The ratio of the dependents (<= 14 years and >= 65 years) divided by the working age (> 15 to 64 years) | 194 | (113) |
| Asset Index | Asset Index constructed from PCA | -0.77 | (1.99) |
| WASH Index | Water, Sanitation and hygiene index constructed from PCA | -0.54 | (1.35) |
| Number of children | Number of children in a household aged 0-59 | 1.92 | (0.83) |
| Dependency ratio | Percentage of number of dependents to the total working-age members in a household. | 194 | (113) |
| Market access [32] | A dummy variable if a household's output and input markets were within LC1 | 0.466 | (0.498) |
| Total off farm income | Total household income from household members salary and wages, excluding crop income in Uganda shillings | 161519 | 1070860 |
| Mother living in the Household | A dummy variable (1= if biological mother of the child was living in the household), 0 if otherwise | 0.89 | (0.31) |

[30] *Dummy variables were not used in the regression*

[31] *The weights used are as follows; 1 for cow, 0.4 for calf, 1.2 for bull and oxen, 0.8 for heifer, 0.1 for goat and sheep, 0.2 for pigs, 0.01 for chicken, 0.07 for broiler, 0.014 for layer, 0.01 for growers, 0.03 for ducks, geese and rabbits*

[32] This is a district level variable

| Variable | Variable definition | Mean | SD |
|---|---|---|---|
| Mother/female head age | Age of the mother of the child or the female head of the household | 35.2 | (11.8) |
| Mother/female school in attendance | A dummy variable (1= if mother or female head never attended school) | 0.22 | (0.41) |
| Change diet | A dummy variable (1= if household involuntarily changed diet to cope with weather extremes e.g drought), 0 if otherwise | 0.22 | (0.41) |
| Savings | A dummy variable (1= if household used savings to cope with weather extremes, | 0.20 | (0.40) |
| Received Govt aid | A dummy variable (1=if household received government aid to cope with weather extremes | 0.01 | (0.10) |
| Relatives & friends | A dummy variable (1= if household received assistance from friends and relatives to cope with weather extremes | 0.09 | (0.29) |
| Non-farm work | A dummy variable (1= if household engaged in more non-farm work during weather extremes | 0.13 | (0.34) |
| Change crops | A dummy variable (1= if household engaged changed crops grown to cope with weather extremes) | 0.05 | (0.22) |
| Farm area | Household total crop farm size in acres | 2.47 | (3.63) |
| Number of crops | Continuous variable on number of crops planted by a household | 4.08 | (1.77) |
| Improved seed use | A dummy variable if household used improved seed | 0.20 | (0.40) |
| Organic fertilizer use | A dummy variable if household used organic fertilizers | 0.12 | (0.32) |
| Inorganic fertilizer use | A dummy variable if household used inorganic fertilizers | 0.04 | (0.21) |
| Pesticide use | A dummy variable if household used pesticide | 0.12 | (0.33) |
| Water harvesting | A dummy variable if household used water harvesting technology | 0.30 | (0.46) |
| ***Weather variables both objective and subjective*** | | | |
| Extreme dry spell SN 1 | A dummy variable (1= if rainfall amounts in the first season of the interview year were < -2 SD, 0 if otherwise | 0.04 | (0.19) |
| Extreme dry spell SN1 (t-1) | A dummy variable (1= if rainfall amounts in the first season of the prior year were < -2 SD, 0 if otherwise | 0.05 | (0.21) |
| Extreme dry spell(5yr) | Counts of extreme dry spell events for both seasons over a 5-year period prior to interview | 0.42 | (1.19) |
| Heat wave SN1 | Monthly counts in the first season of the interview year with temperature values > 1SD | 0.75 | (1.16) |
| Heat wave SN1 (t-1) | Monthly counts in the first season of the prior year with temperature values > 1SD | 0.69 | (1.13) |
| Heat wave (five year) | Monthly counts in the both seasons over five-year period with temperature values > 1SD | 6.13 | (8.09) |

Figure in parenthesis is standard deviation

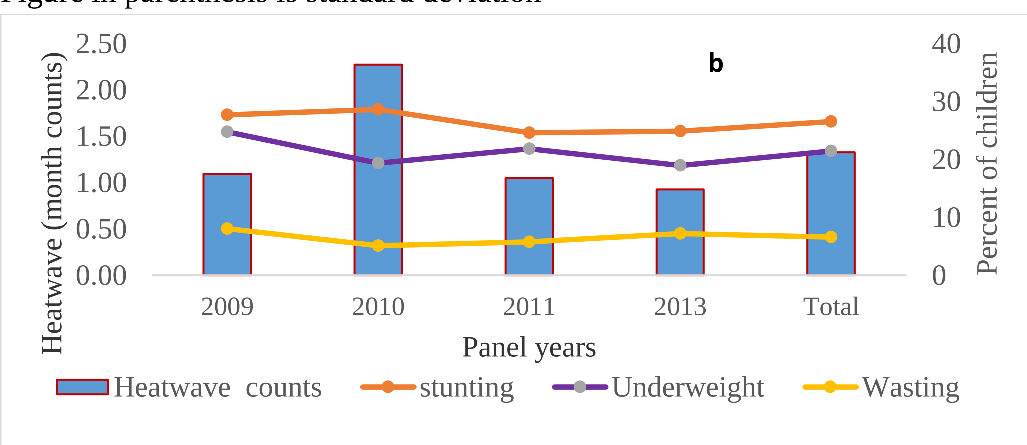


**Figure 7.1**: Relationship between heat wave (t-1) and stunting, wasting and underweight

**Table 7.2:** Extreme weather– crop yield and sales – HAZ relationship (CMP estimates)

| VARIABLES | HAZ | Crop yield (t-1) | Crop sales | HAZ | Crop yield (t-1) | Crop sales (t-1) | HAZ | Crop yield (t-1) | Crop sales (t-1) | HAZ | Crop yield (t-1) | Crop sales (t-1) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Crop yield (t-1) | 0.035 | | | 0.007 | | | -0.010 | | | -0.029 | | |
| | (0.076) | | | (0.074) | | | (0.063) | | | (0.064) | | |
| Crop sales (t-1) | -0.058 | | | -0.040 | | | -0.036 | | | -0.003 | | |
| | (0.289) | | | (0.291) | | | (0.288) | | | (0.289) | | |
| **Extremeweather** | | | | | | | | | | | | |
| Dry spell (5year) | | -0.285*** | -0.043 | | | | | | | | | |
| | | (0.037) | (0.036) | | | | | | | | | |
| Dry spell (t-1) | | | | | -1.465*** | -0.338* | | | | | | |
| | | | | | (0.194) | (0.184) | | | | | | |
| Heatwave (t-1) | | | | | | | | -0.547*** | -0.126*** | | | |
| | | | | | | | | (0.036) | (0.037) | | | |
| Heatwave(5year) | | | | | | | | | | | -0.072*** | -0.019*** |
| | | | | | | | | | | | (0.005) | (0.005) |
| **Adaptation and farm factors** | | | | | | | | | | | | |
| Number of crops | 0.015 | 0.226*** | 0.238*** | 0.022 | 0.233*** | 0.239*** | 0.025 | 0.180*** | 0.228*** | 0.028 | 0.163*** | 0.221*** |
| | (0.030) | (0.025) | (0.031) | (0.029) | (0.025) | (0.031) | (0.027) | (0.024) | (0.031) | (0.027) | (0.024) | (0.032) |
| Crop area | 0.022 | -0.141*** | -0.005 | 0.018 | -0.143*** | -0.005 | 0.016 | -0.129*** | -0.003 | 0.013 | -0.128*** | -0.002 |
| | (0.014) | (0.011) | (0.012) | (0.014) | (0.011) | (0.012) | (0.013) | (0.010) | (0.012) | (0.013) | (0.010) | (0.012) |
| Improved seed | 0.047 | -0.028 | 0.330*** | 0.043 | -0.089 | 0.324** | 0.047 | 0.070 | 0.361*** | 0.045 | 0.087 | 0.375*** |
| | (0.099) | (0.106) | (0.128) | (0.099) | (0.107) | (0.128) | (0.099) | (0.102) | (0.129) | (0.099) | (0.103) | (0.130) |
| Pesticides | -0.007 | 0.219* | 0.535*** | 0.001 | 0.257** | 0.540*** | 0.004 | 0.425*** | 0.580*** | 0.009 | 0.327*** | 0.565*** |
| | (0.124) | (0.131) | (0.197) | (0.124) | (0.131) | (0.197) | (0.123) | (0.125) | (0.199) | (0.123) | (0.126) | (0.199) |
| Organic fertilizer | 0.093 | 0.594*** | 0.214 | 0.108 | 0.604*** | 0.217 | 0.102 | 0.237* | 0.132 | 0.114 | 0.435*** | 0.175 |
| | (0.122) | (0.127) | (0.151) | (0.121) | (0.127) | (0.151) | (0.117) | (0.122) | (0.153) | (0.118) | (0.122) | (0.152) |
| Inorganic fertiliz | -0.256 | 0.135 | 0.810* | -0.252 | 0.144 | 0.792* | -0.246 | 0.168 | 0.785* | -0.249 | 0.088 | 0.787* |
| | (0.177) | (0.207) | (0.429) | (0.177) | (0.207) | (0.431) | (0.178) | (0.197) | (0.431) | (0.177) | (0.199) | (0.436) |
| Water harvesting | | 0.334*** | -0.017 | | 0.352*** | -0.014 | | 0.265*** | -0.035 | | 0.254*** | -0.041 |
| | | (0.093) | (0.098) | | (0.093) | (0.098) | | (0.088) | (0.099) | | (0.089) | (0.099) |
| Cash crop | | | 0.321*** | | | 0.339*** | | | 0.351*** | | | 0.344*** |
| | | | (0.116) | | | (0.115) | | | (0.116) | | | (0.116) |

**Table 7.3:** Average marginal effects of determinants of crop sales

| Variables | Crop sales (t-1) (dy/dx) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dry spell (5year) | -0.009 (0.007) | | | | 0.008 |
| | | | | | (0.009) |
| Dry spell (t-1) | | -0.068* | | | -0.041 |
| | | (0.037) | | | (0.038) |
| Heatwave (t-1) | | | -0.025*** | | -0.009 |
| | | | (0.007) | | (0.010) |
| Heatwave(5year) | | | | -0.004*** | -0.003** |
| | | | | (0.001) | (0.002) |
| **Adaptation and other factors**[33] | | | | | |
| Number of crops | 0.048*** | 0.048*** | 0.045*** | 0.044*** | 0.043*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Crop area | -0.001 | -0.001 | -0.001 | 0.000 | 0.000 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Improved seed | 0.066*** | 0.065** | 0.072*** | 0.074*** | 0.071*** |
| | (0.026) | (0.025) | (0.025) | (0.025) | (0.025) |
| Pesticides | 0.108*** | 0.108*** | 0.115*** | 0.112*** | 0.114*** |
| | (0.040) | (0.040) | (0.039) | (0.039) | (0.039) |
| Organic fertilizer | 0.043 | 0.043 | 0.026 | 0.035 | 0.032 |
| | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) |
| Inorganic fertilizer | 0.163* | 0.159* | 0.156* | 0.156* | 0.154* |
| | (0.086) | (0.086) | (0.085) | (0.086) | (0.084) |
| Water harvesting | -0.003 | -0.003 | -0.007 | -0.008 | -0.007 |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.019) |
| Planted cash crop | 0.065*** | 0.068*** | 0.070*** | 0.068*** | 0.064*** |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| Sequential (base =2) | | | | | |
| 3 | 0.086*** | 0.076*** | 0.063*** | 0.089*** | 0.075*** |
| | (0.019) | (0.020) | (0.020) | (0.019) | (0.022) |
| 4 | 0.067*** | 0.056** | 0.049** | 0.068*** | 0.055** |
| | (0.023) | (0.024) | (0.024) | (0.023) | (0.025) |
| Other variables | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,367 | 1,367 | 1,367 | 1,367 | 1,367 |
| Observations (CMP) | 1615 | 1615 | 1615 | 1615 | 1615 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[33] All these covariates are first lags

**Table 7.4:** Effect of weather extremes on crop, livestock and disease pathways and, on HAZ

| Variables | Crop yield (t-1) | TLU (t-1) | Diarrhoea (t-1) | Fever (t-1) | HAZ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Pathways** | | | | | |
| Crop yield (t-1) | | | | | 0.017 |
| | | | | | (0.064) |
| TLU (t-1) | | | | | 0.225* |
| | | | | | (0.115) |
| Diarrhoea (t-1) | | | | | -1.514*** |
| | | | | | (0.278) |
| Fever (t-1) | | | | | -1.722*** |
| | | | | | (0.240) |
| **Extreme weather events** | | | | | |
| Dry spell (5 year) | -0.062 | -0.383** | 0.006 | 0.016 | |
| | (0.042) | (0.152) | (0.046) | (0.037) | |
| Dry spell[34] (t-1) | -0.817*** | -0.441 | -0.005 | 0.137 | |
| | (0.187) | (0.646) | (0.197) | (0.150) | |
| Heatwave (t-1) | -0.378*** | 0.420* | 0.108** | 0.085** | |
| | (0.050) | (0.226) | (0.053) | (0.041) | |
| Heatwave (5year) | -0.026*** | 0.026 | 0.003 | -0.012* | |
| | (0.008) | (0.028) | (0.008) | (0.006) | |
| **Adaptation strategies** | | | | | |
| Number of crops | 0.158*** | | | | 0.016 |
| | (0.024) | | | | (0.025) |
| Improved seed | 0.063 | | | | 0.036 |
| | (0.100) | | | | (0.094) |
| Pesticides | 0.396*** | | | | -0.028 |
| | (0.123) | | | | (0.122) |
| Organic fertilizers | 0.341*** | | | | 0.090 |
| | (0.121) | | | | (0.116) |
| Inorganic fertilizers | 0.143 | | | | -0.257 |
| | (0.194) | | | | (0.173) |
| Water harvesting | 0.292*** | | | | |
| | (0.088) | | | | |
| Crop area | -0.131*** | | | | 0.016 |
| | (0.010) | | | | (0.013) |
| Constant | 5.845*** | -2.318*** | -0.874 | 0.207 | 0.640 |
| | (0.210) | (0.848) | (0.533) | (0.381) | (0.816) |
| Mean | 6.090 | 2.566 | 0.1123 | 0.357 | -1.119 |
| | (1.831) | (6.974) | (0.315) | (0.479) | (1.373) |
| Log likelihood | -12675 | -12675 | -12675 | -12675 | -12675 |
| Other variables | Yes | Yes | Yes | Yes | Yes |
| Coping strategies | | | | | |
| Observations | 1,799 | 1,799 | 1,799 | 1,799 | 1,799 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[3434] This is for main season, same applies to heatwave (t-1)

**Table 7.5**: Effect of extreme weather events on crop yield and nutrients, and WAZ (2SLS)

| VARIABLES | 1st stage Calories | 2nd stage WAZ | 1st stage Protein | 2nd stage WAZ | 1st stage Zinc (t-1) | 2nd stage WAZ | 1st stage Vitamin A | 2nd stage WAZ | 1st stage Crop yield | 2nd stage WAZ |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| ***Nutrients pathways*** | | | | | | | | | | |
| Calories | | 0.284*** | | | | | | | | |
| | | (0.056) | | | | | | | | |
| Protein | | | | 0.519*** | | | | | | |
| | | | | (0.104) | | | | | | |
| Zinc | | | | | | 0.756*** | | | | |
| | | | | | | (0.154) | | | | |
| Vitamin A | | | | | | | | 0.280*** | | |
| | | | | | | | | (0.067) | | |
| Crop yield | | | | | | | | | | 0.199*** |
| | | | | | | | | | | (0.065) |
| ***Extreme weather events*** | | | | | | | | | | |
| Dry spell (5-year counts) | -0.210*** | | -0.130*** | | -0.098*** | | -0.150*** | | -0.075** | |
| | (0.023) | | (0.019) | | (0.016) | | (0.040) | | (0.030) | |
| Dry spell main season | -0.513*** | | -0.199** | | -0.121* | | 0.614*** | | -0.848*** | |
| | (0.104) | | (0.085) | | (0.071) | | (0.183) | | (0.136) | |
| Heatwave main season | 0.021 | | -0.001 | | -0.009 | | 0.119** | | -0.116*** | |
| | (0.029) | | (0.023) | | (0.019) | | (0.050) | | (0.037) | |
| Heatwave (5-year counts) | -0.025*** | | -0.012*** | | -0.007** | | -0.041*** | | -0.017*** | |
| | (0.005) | | (0.004) | | (0.003) | | (0.008) | | (0.006) | |
| ***Coping strategies*** | | | | | | | | | | |
| Savings | 0.270*** | -0.069 | 0.177*** | -0.085 | 0.114*** | -0.079 | 0.288*** | -0.078 | 0.267*** | -0.036 |
| | (0.052) | (0.059) | (0.043) | (0.062) | (0.036) | (0.064) | (0.092) | (0.065) | (0.068) | (0.059) |
| Non-farm work | -0.267*** | -0.052 | -0.235*** | -0.004 | -0.153*** | -0.011 | -0.077 | -0.112 | -0.372*** | -0.074 |
| | (0.063) | (0.072) | (0.051) | (0.078) | (0.043) | (0.080) | (0.111) | (0.074) | (0.082) | (0.075) |
| Government aid | -0.744*** | 0.361 | -0.461*** | 0.394* | -0.304** | 0.389 | -0.766** | 0.275 | -0.488* | 0.129 |
| | (0.195) | (0.224) | (0.159) | (0.234) | (0.133) | (0.240) | (0.342) | (0.237) | (0.254) | (0.218) |
| Credit access | 0.270** | 0.050 | 0.233** | 0.003 | 0.148* | 0.012 | -0.101 | 0.145 | 0.443*** | 0.045 |
| | (0.125) | (0.137) | (0.102) | (0.143) | (0.085) | (0.147) | (0.220) | (0.146) | (0.163) | (0.139) |
| Sell of assets | 0.121 | 0.088 | 0.028 | 0.109 | -0.032 | 0.148 | 0.017 | 0.124 | -0.082 | 0.150 |
| | (0.102) | (0.111) | (0.083) | (0.115) | (0.070) | (0.118) | (0.180) | (0.119) | (0.134) | (0.111) |
| Involuntary change of diet | -0.166*** | 0.066 | -0.095** | 0.069 | -0.064* | 0.067 | -0.185** | 0.068 | -0.232*** | 0.072 |
| | (0.052) | (0.057) | (0.043) | (0.059) | (0.036) | (0.061) | (0.092) | (0.062) | (0.068) | (0.059) |
| Friends and relatives aid | 0.047 | -0.056 | 0.024 | -0.055 | 0.020 | -0.058 | -0.354*** | 0.058 | -0.156* | -0.019 |
| | (0.072) | (0.078) | (0.058) | (0.080) | (0.049) | (0.083) | (0.126) | (0.088) | (0.093) | (0.079) |

| VARIABLES | 1st stage Calories | 2nd stage WAZ | 1st stage Protein | 2nd stage WAZ | 1st stage Zinc (t-1) | 2nd stage WAZ | 1st stage Vitamin A | 2nd stage WAZ | 1st stage Crop yield | 2nd stage WAZ |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Market access | 0.410*** | -0.049 | 0.240*** | -0.057 | 0.173*** | -0.064 | 0.403*** | -0.026 | 0.369*** | -0.003 |
| | (0.050) | (0.061) | (0.041) | (0.064) | (0.034) | (0.066) | (0.088) | (0.065) | (0.066) | (0.063) |
| Farm area | 0.034*** | 0.001 | 0.029*** | -0.004 | 0.027*** | -0.010 | 0.010 | 0.008 | -0.092*** | 0.029*** |
| Adaptation strategies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| | (0.005) | (0.006) | (0.004) | (0.006) | (0.003) | (0.007) | (0.009) | (0.006) | (0.006) | (0.008) |
| Other variables, year & region | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First stage F statistics [35] of instruments | 94.25*** | | 44.17*** | | 30.38*** | | 24.45*** | | 41.10*** | |
| Endogeneity tests: Durban statistics | 18.14*** | | 21.82*** | | 23.57*** | | 20.20*** | | 7.630*** | |
| Wu-Hausman F statistics | 18.03*** | | 21.70*** | | 23.46*** | | 20.09*** | | 7.563*** | |
| Observations | 3902 | 3902 | 3902 | 3902 | 3902 | 3902 | 3902 | 3902 | 3902 | 3902 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[35] Measures relevance of the instruments

**Table 7.6**: Effect of extreme weather events on crop yield and nutrients, and WHZ (2SLS)

| VARIABLES | 1st stage Calories | 2nd stage WHZ | 1st stage Protein | 2nd stage WHZ | 1st stage Zinc | 2nd stage WHZ | 1st stage Vitamin A | 2nd stage WHZ | 1st stage Crop yield | 2nd stage WHZ |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| ***Nutrients pathway*** | | | | | | | | | | |
| Calories | | 0.299*** | | | | | | | | |
| | | (0.057) | | | | | | | | |
| Protein | | | | 0.534*** | | | | | | |
| | | | | (0.104) | | | | | | |
| Zinc | | | | | | 0.766*** | | | | |
| | | | | | | (0.153) | | | | |
| Vitamin A | | | | | | | | 0.259*** | | |
| | | | | | | | | (0.066) | | |
| Crop yield | | | | | | | | | | 0.292*** |
| | | | | | | | | | | (0.069) |
| ***Extreme weather events*** | | | | | | | | | | |
| Dry spell (5-year counts) | -0.233*** | | -0.150*** | | -0.112*** | | -0.160*** | | -0.098*** | |
| | (0.026) | | (0.021) | | (0.018) | | (0.046) | | (0.034) | |
| Dry spell main season | -0.461*** | | -0.162 | | -0.089 | | 0.681*** | | -0.827*** | |
| | (0.120) | | (0.099) | | (0.083) | | (0.216) | | (0.160) | |
| Heatwave main season | 0.014 | | -0.006 | | -0.013 | | 0.066 | | -0.104** | |
| | (0.032) | | (0.026) | | (0.022) | | (0.058) | | (0.043) | |
| Heatwave (5-year counts) | -0.021*** | | -0.009** | | -0.005 | | -0.038*** | | -0.016** | |
| | (0.005) | | (0.004) | | (0.003) | | (0.009) | | (0.007) | |
| Adaptation and coping | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other variables, year & region | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First stage F statistics [36] of instruments | 73.58*** | | 35.54*** | | 25.16*** | | 19.35*** | | 30.66*** | |
| Endogeneity tests: Durban statistics | 16.12*** | | 21.24*** | | | | 16.29*** | | 16.72*** | |
| Wu-Hausman F statistics | 15.98*** | | 21.09*** | | | | 16.15*** | | 16.57*** | |
| Observations | 3,020 | 3,020 | 3,020 | 3,020 | 3,020 | 3,020 | 3,020 | 3,020 | 3,020 | 3,020 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[36] Measures relevance of the instruments

**Table 7.7**: 2nd stage 2SLS results on the effects of nutrients on WAZ and WHZ, by child sex

| Variables | WAZ | | | | | WHZ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Boys** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Calories | 0.252*** | | | | | 0.232*** | | | | |
| | (0.066) | | | | | (0.069) | | | | |
| Protein | | 0.491*** | | | | | 0.404*** | | | |
| | | (0.124) | | | | | (0.123) | | | |
| Zinc | | | 0.778*** | | | | | 0.609*** | | |
| | | | (0.200) | | | | | (0.191) | | |
| Vitamin A | | | | 0.312*** | | | | | 0.269*** | |
| | | | | (0.094) | | | | | (0.097) | |
| Crop yield | | | | | 0.170** | | | | | 0.214*** |
| | | | | | (0.073) | | | | | (0.080) |
| Observations | 1,976 | 1,976 | 1,976 | 1,976 | 1,976 | 1,555 | 1,555 | 1,555 | 1,555 | 1,555 |
| **Panel B: Girls** | | | | | | | | | | |
| Calories | 0.312*** | | | | | 0.407*** | | | | |
| | (0.102) | | | | | (0.100) | | | | |
| Protein | | 0.514*** | | | | | 0.698*** | | | |
| | | (0.178) | | | | | (0.184) | | | |
| Zinc | | | 0.664*** | | | | | 0.932*** | | |
| | | | (0.238) | | | | | (0.249) | | |
| Vitamin A | | | | 0.237** | | | | | 0.244*** | |
| | | | | (0.099) | | | | | (0.093) | |
| Crop yield | | | | | 0.248* | | | | | 0.444*** |
| | | | | | (0.128) | | | | | (0.134) |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,926 | 1,926 | 1,926 | 1,926 | 1,926 | 1,465 | 1,465 | 1,465 | 1,465 | 1,465 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 7.8**: Effect of extreme weather events on crop output, sales and WAZ – CMP estimates

| Variables | Crop yield (1) | Sold crop (2) | WAZ (3) | Crop yield (4) | Sold crop (5) | WAZ (6) | Crop yield (7) | Sold crop (8) | WAZ (9) | Crop yield (10) | Sold crop (11) | WAZ (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Pathways** | | | | | | | | | | | | |
| Crop yield | | | 0.324*** | | | 0.108* | | | 0.046 | | | 0.168*** |
| | | | (0.069) | | | (0.059) | | | (0.055) | | | (0.053) |
| Crop sales | | | -0.018 | | | -0.096 | | | -0.123 | | | -0.109 |
| | | | (0.211) | | | (0.211) | | | (0.210) | | | (0.209) |
| **Extreme weather events** | | | | | | | | | | | | |
| Dry spell (5 year) | -0.282*** | -0.006 | | | | | | | | | | |
| | (0.044) | (0.020) | | | | | | | | | | |
| Dry spell main season | | | | -2.057*** | -0.234** | | | | | | | |
| | | | | (0.340) | (0.113) | | | | | | | |
| Heatwave main season | | | | | | | -0.667*** | -0.102*** | | | | |
| | | | | | | | (0.052) | (0.023) | | | | |
| Heatwave (5 year) | | | | | | | | | | -0.075*** | -0.013*** | |
| | | | | | | | | | | (0.007) | (0.003) | |
| **Adaptation Interactions** | | | | | | | | | | | | |
| Weather * Crops number | -0.010 | | | -0.090 | | | 0.054*** | | | 0.003* | | |
| | (0.012) | | | (0.077) | | | (0.012) | | | (0.002) | | |
| Weather* Improved seed | -0.072 | | | -0.607* | | | 0.096** | | | 0.001 | | |
| | (0.052) | | | (0.320) | | | (0.046) | | | (0.007) | | |
| Weather *Pesticides | -0.216 | | | 0.681 | | | 0.086 | | | 0.019* | | |
| | (0.137) | | | (0.497) | | | (0.066) | | | (0.011) | | |
| Weather*Organic fertilizer | 0.501*** | | | 2.347*** | | | 0.043 | | | 0.023* | | |
| | (0.079) | | | (0.294) | | | (0.099) | | | (0.012) | | |
| Weather * Inorganic fertilizer | -0.016 | | | -0.710 | | | 0.045 | | | -0.022 | | |
| | (0.205) | | | (0.849) | | | (0.097) | | | (0.021) | | |
| Weather * Water harvesting | 0.129** | | | 1.660*** | | | 0.013 | | | 0.019*** | | |
| | (0.051) | | | (0.247) | | | (0.045) | | | (0.007) | | |
| Weather* Plotarea | 0.005 | | | 0.033 | | | 0.003 | | | -0.001* | | |
| | (0.007) | | | (0.041) | | | (0.005) | | | (0.001) | | |
| Cash crop | | 0.520*** | | | 0.545*** | | | 0.561*** | | | 0.552*** | |
| | | (0.071) | | | (0.071) | | | (0.072) | | | (0.072) | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 5.425*** | 0.130 | -3.735*** | 5.396*** | 0.153 | - | 5.925*** | 0.251* | -2.098*** | 5.808*** | 0.232* | -2.804*** |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 2.439**<br>* | | | | | | |
| | (0.130) | (0.128) | (0.488) | (0.129) | (0.129) | (0.417) | (0.134) | (0.132) | (0.398) | (0.134) | (0.130) | (0.401) |
| /atanhrho_12 | | | -0.383*** | | | -0.099 | | | -0.014 | | | -0.176*** |
| | | | (0.085) | | | (0.076) | | | (0.067) | | | (0.064) |
| /atanhrho_13 | | | -0.141 | | | -0.006 | | | 0.040 | | | -0.027 |
| | | | (0.090) | | | (0.091) | | | (0.087) | | | (0.087) |
| /atanhrho_23 | | | 0.415*** | | | 0.395**<br>* | | | 0.403*** | | | 0.401*** |
| | | | (0.022) | | | 0.022 | | | (0.022) | | | (0.022) |
| Log likelihood | -17234 | -17234 | -17234 | -17239 | -17239 | -17239 | -17192 | -17192 | -17192 | -17176 | -17176 | -17176 |
| Observations | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 7.9:** Effect of extreme weather on crop output, sales and WHZ – CMP estimates

| VARIABLES | Crop yield | Sold crop | WHZ | Crop yield | Sold crop | WHZ | Crop yield | Sold crop | WHZ | Crop yield | Sold crop | WHZ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **Pathways** | | | | | | | | | | | | |
| Crop yield | | | 0.341*** | | | 0.170*** | | | 0.165*** | | | 0.164*** |
| | | | (0.068) | | | (0.063) | | | (0.057) | | | (0.054) |
| Crop sales | | | 0.248 | | | 0.098 | | | 0.100 | | | 0.170 |
| | | | (0.230) | | | (0.239) | | | (0.234) | | | (0.234) |
| **Extreme weather events** | | | | | | | | | | | | |
| Dry spell (5 year) | -0.251*** | -0.005 | | | | | | | | | | |
| | (0.044) | (0.020) | | | | | | | | | | |
| Dry spell main season | | | | -2.037*** | -0.233** | | | | | | | |
| | | | | (0.337) | (0.113) | | | | | | | |
| Heatwave main season | | | | | | | -0.674*** | -0.101*** | | | | |
| | | | | | | | (0.051) | (0.023) | | | | |
| Heatwave (5 year) | | | | | | | | | | -0.074*** | -0.013*** | |
| | | | | | | | | | | (0.007) | (0.003) | |
| **Adaptation Interactions** | | | | | | | | | | | | |
| Weather * Crops number | -0.020* | | | -0.097 | | | 0.055*** | | | 0.003 | | |
| | (0.012) | | | (0.077) | | | (0.012) | | | (0.002) | | |
| Weather * Improved seed | -0.060 | | | -0.628** | | | 0.103** | | | 0.001 | | |
| | (0.052) | | | (0.317) | | | (0.046) | | | (0.007) | | |
| Weather *Pesticides | -0.244* | | | 0.620 | | | 0.093 | | | 0.016 | | |
| | (0.135) | | | (0.492) | | | (0.065) | | | (0.011) | | |
| | Crop yield | Sold crop | WHZ | Crop yield | Sold crop | WHZ | Crop yield | Sold crop | WHZ | Crop yield | Sold crop | WHZ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Weather * Organic fertilizer | 0.547*** | | | 2.413*** | | | 0.019 | | | 0.024** | | |
| | (0.077) | | | (0.291) | | | (0.098) | | | (0.012) | | |
| Weather * Inorganic fertilizer | 0.055 | | | -0.554 | | | 0.055 | | | -0.015 | | |
| | (0.204) | | | (0.842) | | | (0.096) | | | (0.021) | | |
| Weather *Water harvesting | 0.111** | | | 1.610*** | | | 0.013 | | | 0.019*** | | |
| | (0.051) | | | (0.247) | | | (0.045) | | | (0.007) | | |
| Planted cash crop | | 0.511*** | | | 0.537*** | | | 0.551*** | | | 0.541*** | |
| | | (0.071) | | | (0.071) | | | (0.071) | | | (0.071) | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Log likelihood | | | -15373 | | | -15378 | | | -15329 | | | -15317 |
| Observations | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 | 4,800 |

**Table 7.10**: Effect of weather extremes on WAZ and WHZ through livestock pathway (3SLS)

| | WAZ | | | WHZ | | |
|---|---|---|---|---|---|---|
| **Variables** | Crop yield | TLU | WAZ | Crop yield | TLU | WHZ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Pathways** | | | | | | |
| Crop yield | | | 0.280** | | | 0.280*** |
| | | | (0.132) | | | (0.106) |
| TLU | | | 0.332** | | | 0.208** |
| | | | (0.152) | | | (0.105) |
| **Extreme weather events** | | | | | | |
| Dry spell counts (5 year) | -0.064** | -0.298*** | | -0.084*** | -0.359*** | |
| | (0.029) | (0.099) | | (0.032) | (0.128) | |
| Dry spell | -0.601*** | 0.365 | | -0.541*** | 0.494 | |
| | (0.139) | (0.370) | | (0.160) | (0.552) | |
| Heat wave | -0.310*** | 0.376*** | | -0.309*** | 0.394*** | |
| | (0.036) | (0.111) | | (0.040) | (0.148) | |
| 5-year heatwave | -0.033*** | 0.021 | | -0.030*** | 0.033 | |
| | (0.006) | (0.014) | | (0.006) | (0.021) | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 5.670*** | -1.094* | -3.268*** | 5.684*** | -1.266* | -3.574*** |
| | (0.146) | (0.572) | (0.711) | (0.167) | (0.691) | (0.603) |
| Observations | 3,902 | 3,902 | 3,902 | 3,020 | 3,020 | 3,020 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 7.11**: Effect of extreme weather events on, diarrhoea and fever on WAZ

| Variables | Diarrhoea | Fever | WAZ | Diarrhoea | Fever | WAZ | Diarrhoea | Fever | WAZ | Diarrhoea | Fever | WAZ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **Pathways** | | | | | | | | | | | | |
| Diarrhoea | | | -0.743*** | | | -0.543** | | | -0.468* | | | -0.604** |
| | | | (0.258) | | | (0.258) | | | (0.255) | | | (0.244) |
| Fever | | | 0.560** | | | -1.111*** | | | -1.083*** | | | -1.113*** |
| | | | (0.280) | | | (0.331) | | | (0.354) | | | (0.328) |
| **Extreme weather** | | | | | | | | | | | | |
| Dry spell counts (5 year) | 0.086*** | -0.076*** | | | | | | | | | | |
| | (0.020) | (0.019) | | | | | | | | | | |
| Dry spell | | | | 0.190 | 0.029 | | | | | | | |
| | | | | (0.130) | (0.098) | | | | | | | |
| Heat wave | | | | | | | 0.072*** | 0.014 | | | | |
| | | | | | | | (0.026) | (0.019) | | | | |
| 5-year heatwave | | | | | | | | | | 0.017*** | 0.001 | |
| | | | | | | | | | | (0.003) | (0.003) | |
| Constant | -1.005*** | -0.090 | -2.099*** | -1.037*** | -0.071 | -1.359*** | -1.053*** | -0.076 | -1.387*** | -1.027*** | -0.069 | -1.345*** |
| | (0.312) | (0.212) | (0.285) | (0.311) | (0.212) | (0.296) | (0.312) | (0.212) | (0.302) | (0.312) | (0.212) | (0.294) |
| /atanhrho_12 | | | 0.158 | | | 0.069 | | | 0.039 | | | 0.094 |
| | | | (0.100) | | | (0.096) | | | (0.095) | | | (0.092) |
| /atanhrho_13 | | | -0.315** | | | 0.475*** | | | 0.461*** | | | 0.475*** |
| | | | (0.131) | | | (0.160) | | | (0.171) | | | (0.158) |
| /atanhrho_23 | | | -0.004 | | | -0.008 | | | -0.009 | | | -0.004 |
| | | | (0.035) | | | (0.035) | | | (0.035) | | | (0.035) |
| Log likelihood | | | -11982 | | | | | | -11993 | | | -11985 |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean | 0.085 | 0.294 | -1.034 | 0.085 | 0.294 | -1.034 | 0.085 | 0.294 | -1.034 | 0.085 | 0.294 | -1.034 |
| | (0.278) | (0.455) | (1.316) | (0.278) | (0.455) | (1.316) | (0.278) | (0.455) | (1.316) | (0.278) | (0.455) | (1.316) |
| Observations | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 7.12**: Effect of extreme weather events on diarrhoea and fever on WHZ

| VARIABLES | Diarrhoea | Fever | WHZ | Diarrhoea | Fever | WHZ | Diarrhoea | Fever | WHZ | Diarrhoea | Fever | WHZ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **Pathways** | | | | | | | | | | | | |
| Diarrhoea | | | -0.440 | | | -0.240 | | | -0.234 | | | -0.509 |
| | | | (0.342) | | | (0.323) | | | (0.318) | | | (0.338) |
| Fever | | | 0.683*** | | | -1.102*** | | | -1.176*** | | | -1.156*** |
| | | | (0.254) | | | (0.246) | | | (0.216) | | | (0.225) |
| **Extreme weather** | | | | | | | | | | | | |
| Dry spell counts (5 year) | 0.083*** | -0.076*** | | | | | | | | | | |
| | (0.020) | (0.018) | | | | | | | | | | |
| Dry spell | | | | 0.184 | 0.040 | | | | | | | |
| | | | | (0.131) | (0.099) | | | | | | | |
| Heat wave | | | | | | | 0.073*** | 0.034* | | | | |
| | | | | | | | (0.026) | (0.019) | | | | |
| 5-year heatwave | | | | | | | | | | 0.017*** | 0.003 | |
| | | | | | | | | | | (0.003) | (0.003) | |
| Constant | -0.930*** | -0.094 | -2.304*** | -1.002*** | -0.024 | -1.492*** | -1.033*** | -0.038 | -1.456*** | -0.982*** | -0.019 | -1.411*** |
| | (0.308) | (0.212) | (0.333) | (0.307) | (0.212) | (0.328) | (0.308) | (0.212) | (0.325) | (0.308) | (0.212) | (0.326) |
| /atanhrho_12 | | | 0.123 | | | 0.033 | | | 0.030 | | | 0.143 |
| | | | (0.140) | | | (0.126) | | | (0.123) | | | (0.134) |
| /atanhrho_13 | | | -0.415*** | | | 0.532*** | | | 0.574*** | | | 0.561*** |
| | | | (0.135) | | | (0.134) | | | (0.119) | | | (0.123) |
| /atanhrho_23 | | | -0.008 | | | -0.018 | | | -0.019 | | | -0.017 |
| | | | (0.035) | | | (0.035) | | | (0.035) | | | (0.035) |
| Other variables | | | | | | | | | | | | |
| Year & year fixed effects | | | | | | | | | | | | |
| Log likelihood | -9822 | -9822 | -9822 | -9836 | -9836 | -9836 | -9831 | -9831 | -9831 | -9824 | -9824 | -9824 |
| Observations | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 7.13** Effect of extreme weather events on diarrhoea and fever on WAZ and WHZ, with all extreme weather events

| Variables | Diarrhoea | Fever | WAZ | Diarrhoea | Fever | WHZ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Pathways** | | | | | | |
| Diarrhoea | | | -0.675*** | | | -0.547 |
| | | | (0.258) | | | (0.346) |
| Fever | | | 0.693*** | | | 0.658** |
| Extreme weather events | | | | | | |
| | | | (0.239) | | | (0.262) |
| Dry spell counts (5 year) | 0.029 | -0.113*** | | 0.025 | -0.105*** | |
| | (0.028) | (0.022) | | (0.028) | (0.022) | |
| Dry spell | -0.042 | 0.002 | | -0.040 | 0.011 | |
| | (0.141) | (0.105) | | (0.141) | (0.106) | |
| Heat wave | -0.025 | 0.022 | | -0.023 | 0.010 | |
| | (0.037) | (0.026) | | (0.037) | (0.026) | |
| 5-year heatwave | 0.016*** | 0.007* | | 0.017*** | 0.0067 | |
| | (0.006) | (0.004) | | (0.006) | (0.004) | |
| Constant | -1.003*** | -0.120 | -2.179*** | -0.946*** | -0.111 | -2.271*** |
| | (0.314) | (0.213) | (0.277) | (0.309) | (0.213) | (0.334) |
| /atanhrho_12 | | | 0.129 | | | 0.170 |
| | | | (0. 099) | | | (0.144) |
| /atanhrho_13 | | | -0.379 | | | -0.401*** |
| | | | (0.113) | | | (0.140) |
| /atanhrho_23 | | | -0.007 | | | -0.012 |
| | | | (0.035) | | | (0.035) |
| Log likelihood | | | -11973 | -9814 | -9814 | -9814 |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 | 5,132 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

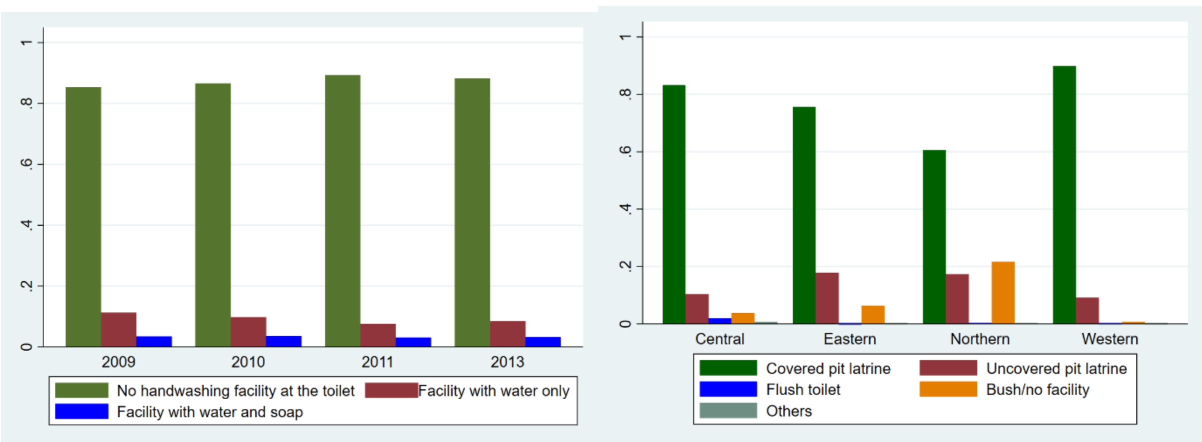


**Figure 7.2**: Proportion of HHs using different hygiene practices and sanitation facilities.

**Table 7.14** AME of logit and two-part models on effect of weather and determinants of illness (*with extreme weather variables*)

| | Women | | | | Men | | | |
|---|---|---|---|---|---|---|---|---|
| | Logit | | TPM | | Logit | | TPM | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Negative rain deviation | 0.0806*** | | 0.999*** | | 0.0647*** | | 0.313* | |
| | (0.0137) | | (0.205) | | (0.0134) | | (0.179) | |
| Extreme negative rain | | 0.0914*** | | 1.177*** | | 0.0644*** | | 0.730*** |
| | | (0.0147) | | (0.209) | | (0.0137) | | (0.182) |
| Log monthly rain | -0.0212 | -0.0189 | -0.379 | -0.398 | -0.0689** | -0.0619* | -0.566 | -0.560 |
| | (0.0354) | (0.0354) | (0.502) | (0.500) | (0.0335) | (0.0335) | (0.459) | (0.459) |
| Log rainfall squared | 0.0050 | 0.0048 | 0.071 | 0.074 | 0.0100** | 0.0092** | 0.083 | 0.084 |
| | (0.0046) | (0.0046) | (0.065) | (0.065) | (0.0043) | (0.0043) | (0.059) | (0.059) |
| Positive temperature | 0.0199** | | 0.175 | | 0.0214** | | 0.244* | |
| | (0.0098) | | (0.142) | | (0.0093) | | (0.125) | |
| Extreme positive temp | | 0.0282*** | | 0.376** | | 0.0091 | | 0.139 |
| | | (0.0110) | | (0.157) | | (0.0104) | | (0.139) |
| Monthly temperature | 0.0361*** | 0.0333** | 0.458** | 0.406** | 0.0439*** | 0.0453*** | 0.330* | 0.333 |
| | (0.0125) | (0.0125) | (0.185) | (0.184) | (0.0127) | (0.0127) | (0.180) | (0.180) |
| Temperature squared | -0.0005** | -0.0005** | -0.007** | -0.006* | -0.0006*** | -0.0007*** | -0.005 | -0.005 |
| | (0.0002) | (0.0002) | (0.003) | (0.003) | (0.0002) | (0.0002) | (0.003) | (0.003) |
| Water harvesting | 0.014 | 0.014 | 0.207 | 0.224 | -0.101** | -0.104** | -1.032* | -1.010* |
| | (0.037) | (0.037) | (0.536) | (0.537) | (0.042) | (0.042) | (0.568) | (0.566) |
| Improved water source | -0.007 | -0.012 | -0.153 | -0.204 | -0.013 | -0.019** | -0.110 | -0.149 |
| | (0.010) | (0.010) | (0.141) | (0.141) | (0.009) | (0.009) | (0.126) | (0.125) |
| Other water source | -0.011 | -0.007 | 1.055 | 1.070 | 0.039 | 0.041 | 0.793 | 0.801 |
| | (0.057) | (0.057) | (0.780) | (0.770) | (0.049) | (0.050) | (0.645) | (0.652) |
| Treated drinking water | -0.054** | -0.056** | -0.490 | -0.497 | -0.007 | -0.007 | 0.127 | 0.106 |
| | (0.024) | (0.024) | (0.331) | (0.330) | (0.023) | (0.023) | (0.311) | (0.313) |
| | (0.014) | (0.015) | (0.198) | (0.220) | (0.013) | (0.014) | (0.175) | (0.193) |
| 2nd quarter of the year | -0.028** | -0.032 | -0.186 | -0.227 | -0.049** | -0.051*** | -0.475*** | -0.521*** |
| | (0.014) | (0.014) | (0.205) | (0.205) | (0.014) | (0.014) | (0.184) | (0.184) |
| 3rd quarter of the year | -0.010 | -0.013 | -0.037 | -0.060 | 0.001 | 0.000 | -0.030 | -0.067 |
| | (0.013) | (0.013) | (0.190) | (0.190) | (0.013) | (0.013) | (0.168) | (0.168) |
| 4th quarter of the year | 0.029** | 0.027 | 0.245 | 0.217 | 0.038*** | 0.037*** | 0.345** | 0.319* |
| | (0.013) | (0.013) | (0.192) | (0.192) | (0.013) | (0.013) | (0.170) | (0.171) |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mediator variables | No | No | No | No | No | No | No | No |
| N | 11,567 | 11,567 | 11,567 | 11,567 | 10,901 | 10,901 | 10,901 | 10,901 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 7.15**: Effect of weather variables (with weather extremes) on time spent on water collection

| | Women GLM | | | | Men GLM | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std. Err. | Coefficient | Std. Err. | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Negative rain deviation | 0.5844*** | (0.1755) | - | - | 0.2076 | (0.1344) | - | - |
| Extreme negative rain | | | 0.9374*** | (0.2233) | - | - | -0.0330 | (0.1825) |
| Log monthly rain | -1.5584*** | (0.4260) | -1.4972*** | (0.4247) | 1.2852*** | (0.3477) | 1.2785*** | (0.3476) |
| Log rainfall squared | 0.2267*** | (0.0549) | 0.2221*** | (0.0548) | -0.1601*** | (0.0455) | -0.1597*** | (0.0456) |
| Positive temperature | -0.4399*** | (0.1354) | - | - | -0.1477 | (0.1031) | - | - |
| Extreme positive temp | | | -0.6949*** | (0.1587) | - | - | 0.0804 | (0.1230) |
| Monthly temperature | 0.3750** | (0.1477) | 0.3525** | (0.1496) | 0.1410 | (0.1291) | 0.1364 | (0.1301) |
| Temperature squared | -0.0037 | (0.0024) | -0.0032 | (0.0024) | -0.0022 | (0.0021) | -0.0021 | (0.0021) |
| Water harvesting | -3.211*** | (0.773) | -3.384*** | (0.763) | -2.163*** | (0.561) | -2.175*** | (0.559) |
| Improved water source | 0.483*** | (0.126) | 0.464*** | (0.126) | -0.036 | (0.110) | -0.021 | (0.107) |
| Other water source | -3.493*** | (0.771) | -3.549*** | (0.755) | -0.215 | (0.632) | -0.193 | (0.638) |
| Treated drinking water | -0.789** | (0.348) | -0.781** | (0.354) | 0.154 | (0.253) | 0.116 | (0.252) |
| 2nd quarter of the year | -0.287 | (0.192) | -0.348* | (0.194) | -0.344** | (0.145) | -0.332** | (0.146) |
| 3rd quarter of the year | 0.369** | (0.178) | 0.368** | (0.177) | -0.289** | (0.132) | -0.293** | (0.131) |
| 4th quarter of the year | -0.011 | (0.184) | 0.003 | (0.185) | -0.165 | (0.139) | -0.165 | (0.139) |
| Other variables | Yes | | Yes | | Yes | | Yes | |
| Year variables | Yes | | Yes | | Yes | | Yes | |
| N | 11,567 | | 11,567 | | 10,901 | | 10,901 | |

Standard errors in parentheses ***
p<0.01, ** p<0.05, * p<0.1

**Table 7.16**: Effect of weather on days of illness and work days lost (HNBM & NBM)

| | All sample | | | Women | | | Men | | |
|---|---|---|---|---|---|---|---|---|---|
| Variables | Logit | Truncated NB | Negbin | Logit | Truncated NB | Negbin | Logit | Truncated NB | Negbin |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Panel A** | | | | Days illness | | | | | |
| Negative rainfall deviation | 0.075*** | -0.198 | 0.932*** | 0.083*** | 0.552 | 1.364*** | 0.067*** | -1.251** | 0.562** |
| | (0.009) | (0.313) | (0.202) | (0.014) | (0.403) | (0.303) | (0.013) | (0.494) | (0.264) |
| Log month rainfall | -0.044* | -0.106 | -0.576 | -0.022 | -0.330 | -0.282 | -0.062* | 0.384 | -0.742 |
| | (0.025) | (0.744) | (0.503) | (0.035) | (0.962) | (0.739) | (0.034) | (1.168) | (0.674) |
| Log rain squared | 0.007*** | 0.011 | 0.089 | 0.005 | 0.041 | 0.067 | 0.009** | -0.054 | 0.097 |
| | (0.003) | (0.096) | (0.065) | (0.005) | (0.124) | (0.095) | (0.004) | (0.151) | (0.086) |
| Positive temperature deviation | 0.022*** | 0.010 | 0.272* | 0.020** | -0.044 | 0.159 | 0.023** | 0.137 | 0.337* |
| | (0.007) | (0.212) | (0.140) | (0.009) | (0.277) | (0.209) | (0.009) | (0.329) | (0.186) |
| Month temperature | 0.043*** | -0.025 | 0.518*** | 0.039*** | 0.254 | 0.556** | 0.048*** | -0.366 | 0.489* |
| | (0.009) | (0.279) | (0.180) | (0.012) | (0.349) | (0.258) | (0.013) | (0.462) | (0.251) |
| Temperature squared | -0.001*** | 0.000 | -0.008*** | -0.001*** | -0.004 | -0.008** | -0.001*** | 0.005 | -0.007* |
| | (0.000) | (0.004) | (0.003) | (0.000) | (0.006) | (0.004) | (0.000) | (0.007) | (0.004) |
| Sex | -0.070*** | -0.376* | -0.846*** | | | | | | |
| | (0.006) | (0.201) | (0.134) | | | | | | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 22,468 | 6,970 | 22,468 | 11,567 | 4134 | 11,567 | 10,901 | 2386 | 10,901 |
| **Panel B** | | | | **Work days lost due to illness** | | | | | |
| Negative rainfall deviation | 0.068*** | -0.850*** | 0.400*** | 0.080*** | -0.861*** | 0.488*** | 0.056*** | -0.798* | 0.310** |
| | (0.009) | (0.270) | (0.110) | (0.013) | (0.331) | (0.159) | (0.012) | (0.460) | (0.153) |
| Log month rainfall | 0.020 | 0.381 | 0.093 | 0.036 | 1.348* | 0.562 | 0.005 | -1.298 | -0.279 |
| | (0.023) | (0.650) | (0.265) | (0.034) | (0.797) | (0.374) | (0.032) | (1.120) | (0.378) |
| Log rain squared | -0.002 | -0.041 | -0.007 | -0.003 | -0.164 | -0.060 | 0.000 | 0.164 | 0.033 |
| | (0.003) | (0.083) | (0.034) | (0.004) | (0.102) | (0.048) | (0.004) | (0.144) | (0.049) |
| Positive temperature deviation | 0.013** | 0.007 | 0.084 | 0.016* | -0.025 | 0.053 | 0.009 | 0.089 | 0.106 |
| | (0.006) | (0.180) | (0.075) | (0.009) | (0.224) | (0.108) | (0.008) | (0.302) | (0.105) |
| Month temperature | 0.027*** | -0.113 | 0.180* | 0.019 | -0.159 | 0.128 | 0.038*** | 0.045 | 0.226 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (0.008) | (0.235) | (0.096) | (0.012) | (0.280) | (0.134) | (0.012) | (0.423) | (0.138) |
| Temperature squared | 0.000*** | 0.002 | -0.003* | 0.000 | 0.003 | -0.002 | -0.001*** | -0.001 | -0.004* |
| | (0.000) | (0.004) | (0.002) | (0.000) | (0.004) | (0.002) | (0.000) | (0.007) | (0.002) |
| Sex | -0.049*** | 0.437** | -0.275*** | | | | | | |
| | (0.006) | (0.172) | (0.071) | | | | | | |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 22,468 | 5,083 | 22,468 | 11,567 | 3,027 | 11,567 | 10,901 | 2,056 | 10,901 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 7.17**: Multivariate decomposition results for days of illness at the intensive margin

| VARIABLES | Days illness (number) | |
|---|---|---|
| **Overall decomposition** | Coefficients | Percentage |
| Characteristics (E) – Explained | 0.196** | 56.83 |
| | (0.091) | |
| Coefficients (C) – Unexplained | 0.149 | 43.17 |
| | (0.2200 | |
| Raw difference | 0.345* | |
| | (0.205) | |
| **Detailed decomposition (E)** | E | |
| Distance to the health facilities | 0.0495*** | 14.35 |
| | (0.0070) | |
| Other health care | 0.0055*** | 1.593 |
| | (0.0019) | |
| Government hospital/centre | 0.0243* | 7.057 |
| | (0.0136) | |
| Private hospital/doctor | -0.0131** | -3.785 |
| | (0.0065) | |
| Pharmacy or drug/local shop | 0.0715*** | 20.737 |
| | (0.0096) | |
| Negative rainfall deviation | -0.0030 | -0.874 |
| | (0.0055) | |
| Other variables | Yes | Yes |
| Observations | 6,971 | 6,971 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

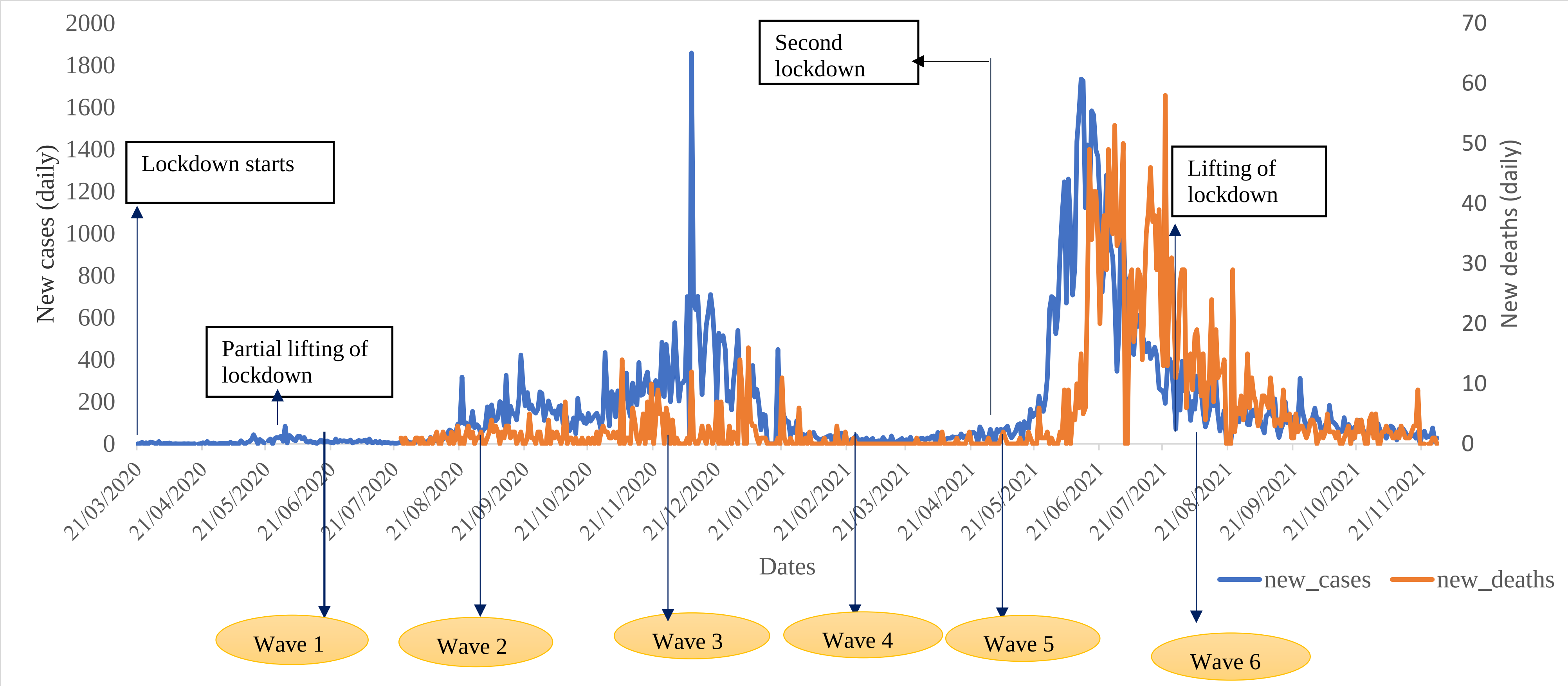


Figure 7.3: Number of COVID-19 daily cases and deaths in Uganda, and survey timelines.

Source: adapted from John Hopkins University data

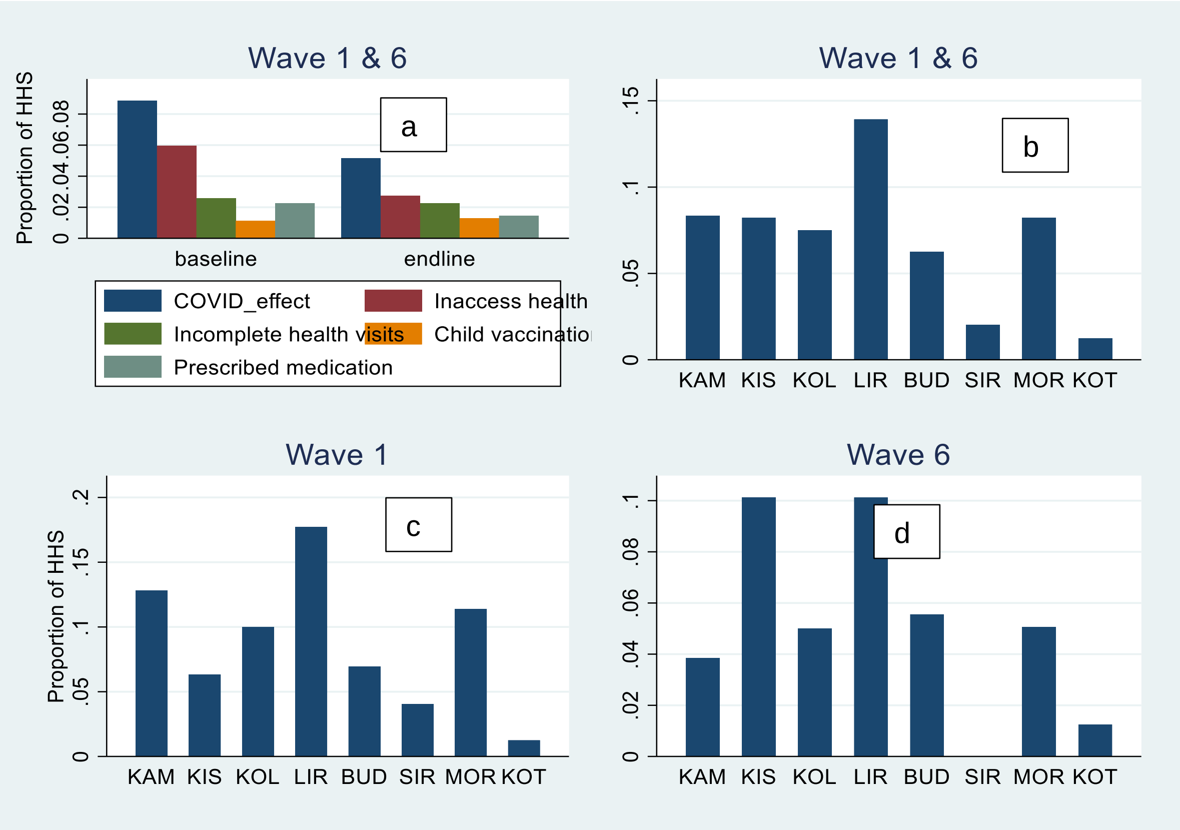


**Figure 7.4**: Proportion of households affected by COVID lockdown in terms of health care access in wave 1 and 6 (a), and affected households by districts sampled (b, c, and d)

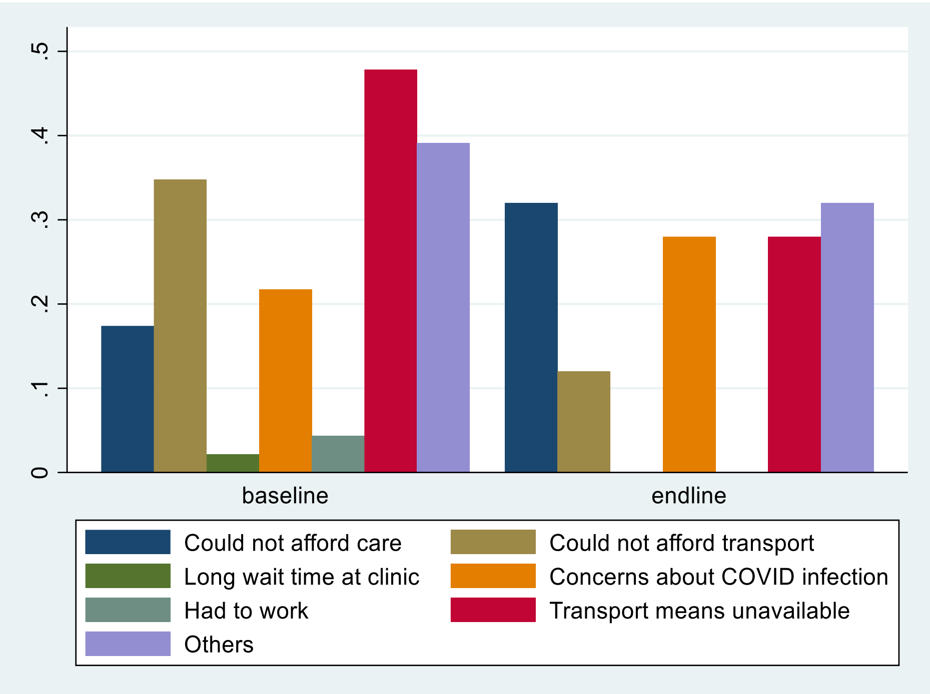


**Figure 7.5**: Reasons why households could not access health services - subsample analysis

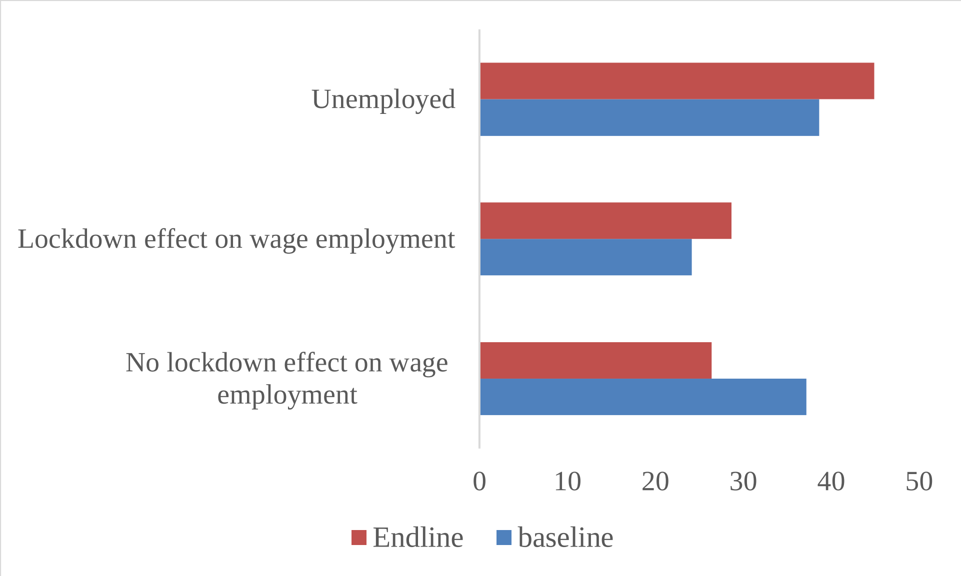


Figure 7.6: Percentage of households affected & unaffected by lockdown, and unemployed [37]

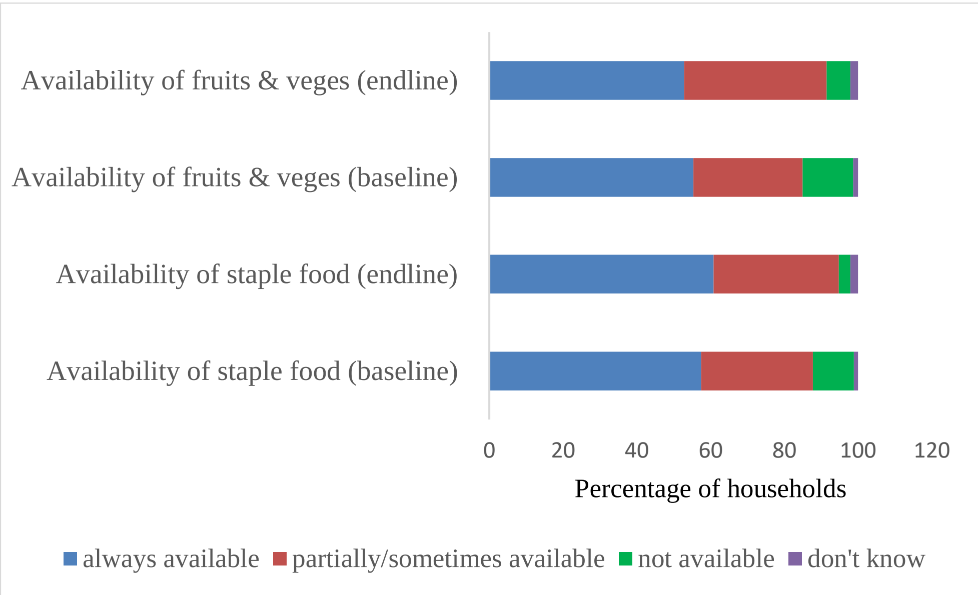


**Figure 7.7**: Availability of staple food, fruits and vegetables at local market during lockdown

[37] The sample size in either wave 621. The affected and unaffected households were employed during the recall period.

**Table 7.18**: Selected households characteristics by poverty transition (wave 2 and Wave 4), and (wave 3 and 6)

| | **Always non- poor** | | **Always non- poor** | | **Always poor** | | **Always poor** | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Wave 2** | **Wave 4** | **Wave 3** | **Wave 6** | **Wave 2** | **Wave 4** | **Wave 3** | **Wave 6** |
| | (N= 431) | (N= 431) | (N= 451) | (N= 451) | (N= 60) | (N= 60) | (N= 80) | (N= 80) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Household size | 6.65 (2.55) | 6.74 (2.70) | 6.86 (2.63) | 6.53 (2.69) * | 7.3 (2.32) | 6.82 (2.08) | 7.1 (1.99) | 6.8 (2.03) |
| Asset value | 6,995,687 | 6,400,858 | 6,949,995 | 7,469,445 | 1,382,825 | 1,156,833 | 1,049,191 | 746,988 |
| | (13,165,645) | 9920997 | (11,840,185) | (12,712,456) | (1,447,686) | (1,696,593) | (1,729,084) | (1,075,402) |
| Asset ownership (1= Female) | 37.82 | 36.89 | 34 | 30 | 85.00 | 78.33 | 83 | 75 |
| Livestock value | 1,696,805 | 1,715,587 | 1,710,184 | 1,643,236 | 2,448,733 | 2,578,300 | 3,211,525 | 1,288,000 |
| | (2,549,603) | (2,388,193) | (2,532,059) | (2,318,149) | (5,776,194) | (5,680,380) | (1.08e+07) | (2,435,615) |
| Membership any group (%) | 84 | 87 | 78 | 84** | 53 | 43 | 44 | 28** |
| Health or wellbeing group (%) | 7 | 23*** | 19 | 31*** | 3 | 8 | 6 | 10 |
| Financial group (%) | 65 | 72** | 60 | 69*** | 33 | 23 | 31 | 11*** |
| Loan income (%) | 4 | 4 | 5 | 4 | 5 | 2 | 1 | 1 |
| Remittances (%) | 4 | 6 | 5 | 6 | 2 | 5 | 3 | 0 |
| Paid labor force participation (%) | 69 | 64 | 58 | 62 | 47 | 33 | 29 | 26 |
| Wage income (UGX) | 308, 013 | 349,930 | 27, 9851 (797, | 264, 459 | 114, 367 | 77, 683 | 65, 175 | 27,175 |
| | (716,685) | (713,763) | 006) | (569, 059) | (258,235) | (187833) | (195, 543) | (84, 144) |
| Household diet diversity | 8.05 | 8.035 | 7.76 | 7.48 | 5.167 | 4.633 | 4.88 | 4.64 |
| | (1.89) | (2.040) | (1.95) | (2.08) ** | (1.43) | (1.178) ** | (1.21) | (1.01) |
| Rainfall Z scores (2 months) | 0.919 | 0.609 | 1.404 | -0.544 | 0.352 | -0.722 | -0.624 | -0.973 (0.377) *** |
| | (2.076) | (1.302) *** | (1.463) | (0.914) *** | (1.043) | (1.027) *** | (0.689) | |
| Temperature Z scores (2 months) | -0.494 | -0.572 | -0.598 | -0.068 | 0.037 | 0.554 (0.874) | 0.337 | 0.799 (0.929) *** |
| | (0.832) | (0 .879) | (0.712) | (1.067) *** | (0.749) | *** | (0.763) | |
| Extreme temperature (%) | 1 | 3* | 0 | 15*** | 0 | 47*** | 16 | 55*** |
| HHs member sick (%) | 83 | 75*** | 79 | 68*** | 77 | 53*** | 59 | 38*** |
| HHs number of sick days | 17 (21) | 13(17) *** | 17(19) | 11(14) *** | 13 (17) | 7(9) ** | 8 (12) | 3 (6) *** |
| HH member sick more than 30 days (%) | 12 | 9 | 13 | 6*** | 7 | 2 | 3 | 1 |
| Household member hospitalized (%) | 21 | 16* | 21 | 12*** | 18 | 10 | 9 | 4 |
| Death of hhs member (%) | 0.5 | 1.39 | 2 | 0.67* | 1.7 | 1.7 | 1.25 | 0 |
| Total health expenditures (UGX) | 63,059 | 47, 869 | 53,718 | 49,766 | 18, 067 | 5,625 | 12,343 | 2,350 (13,975) *** |
| | (139,476) | (109,719) * | (114,234) | (139,952) | (59,368) | (22, 356) | (31,051) | |
| Free medical services | 22 | 17* | 16 | 12** | 52 | 37* | 36 | 29 |

Standard deviations in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 7.19**: Effect of illness & weather on consumption (Fixed effects without interactions)

| | Total consumption | | | Food consumption | | | Non-food consumption | | |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| HHs member sick > 30 days | 0.008 | | | 0.035 | | | -0.088* | | |
| | (0.030) | | | (0.030) | | | (0.051) | | |
| Days of illness | | 0.001* | | | 0.001** | | | -0.001 | |
| | | (0.001) | | | (0.001) | | | (0.001) | |
| Hospitalized | | | 0.041* | | | 0.027 | | | 0.087** |
| | | | (0.023) | | | (0.023) | | | (0.041) |
| Extreme high rain | -0.132*** | -0.133*** | -0.133*** | -0.127*** | -0.128*** | -0.128*** | -0.111** | -0.110** | -0.112** |
| | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) | (0.048) | (0.048) | (0.048) |
| Extreme high temperature | -0.130*** | -0.130*** | -0.126*** | -0.097*** | -0.097*** | -0.094*** | -0.189*** | -0.192*** | -0.186*** |
| | (0.035) | (0.035) | (0.035) | (0.035) | (0.034) | (0.035) | (0.060) | (0.060) | (0.060) |
| Extreme low rain | -0.004 | -0.002 | -0.003 | 0.026 | 0.026 | 0.024 | -0.028 | -0.024 | -0.022 |
| | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) | (0.077) | (0.077) | (0.077) |
| Wave fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| HHs fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 | 3,726 |
| R-squared | 0.114 | 0.115 | 0.115 | 0.131 | 0.132 | 0.131 | 0.110 | 0.109 | 0.110 |
| Number of HHID | 621 | 621 | 621 | 621 | 621 | 621 | 621 | 621 | 621 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 7.20**: Effect of change in household health, weather shocks and interactions on consumption (FD model)

| VARIABLES | D.Total consumption | | | D. Food consumption | | | D. Non-food consumption | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| D.HHs member sick 30 days | -0.009 | | | 0.020 | | | -0.091 | | |
| | (0.037) | | | (0.038) | | | (0.062) | | |
| D. Days of illness | | 0.000 | | | 0.001 | | | -0.001 | |
| | | (0.001) | | | (0.001) | | | (0.001) | |
| D.Hospitalized | | | 0.049** | | | 0.037 | | | 0.102** |
| | | | (0.025) | | | (0.025) | | | (0.043) |
| D.Extreme rain | -0.082*** | -0.082*** | -0.083*** | -0.071*** | -0.072*** | -0.072*** | -0.111** | -0.109** | -0.113** |
| | (0.027) | (0.027) | (0.028) | (0.027) | (0.027) | (0.027) | (0.045) | (0.045) | (0.045) |
| D.Extreme temperature | 0.025 | 0.023 | 0.024 | 0.144*** | 0.143*** | 0.142*** | -0.249*** | -0.273*** | -0.253*** |
| | (0.051) | (0.051) | (0.051) | (0.052) | (0.051) | (0.052) | (0.095) | (0.098) | (0.097) |
| D.sick_30days#D. extreme rain | 0.038 | | | 0.042 | | | 0.056 | | |
| | (0.060) | | | (0.059) | | | (0.098) | | |
| D.sick_30days#D. extreme temp | -0.028 | | | -0.042 | | | -0.435* | | |
| | (0.130) | | | (0.134) | | | (0.248) | | |
| D. illness#D. extreme rain | | 0.002 | | | 0.001 | | | 0.003* | |
| | | (0.001) | | | (0.001) | | | (0.002) | |
| D. days of illness #D. extreme temp | | -0.001 | | | -0.001 | | | -0.009** | |
| | | (0.002) | | | (0.003) | | | (0.004) | |
| D.hospitalized#D.extreme rain | | | 0.020 | | | 0.001 | | | 0.054 |
| | | | (0.052) | | | (0.053) | | | (0.088) |
| D.Hospitalized#D.extreme_temp | | | -0.054 | | | -0.087 | | | -0.127 |
| | | | (0.110) | | | (0.098) | | | (0.209) |
| D.household size | -0.126*** | -0.127*** | -0.127*** | -0.138*** | -0.138*** | -0.137*** | -0.085*** | -0.086*** | -0.091*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.025) | (0.025) | (0.025) |
| D. assets value (log) | 0.075*** | 0.073*** | 0.074*** | 0.044*** | 0.043*** | 0.044*** | 0.116*** | 0.116*** | 0.113*** |
| | (0.015) | (0.015) | (0.015) | (0.014) | (0.014) | (0.014) | (0.028) | (0.028) | (0.028) |
| D. livestock value (log) | 0.008*** | 0.009*** | 0.009*** | 0.010*** | 0.010*** | 0.010*** | 0.004 | 0.004 | 0.004 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.005) | (0.005) | (0.005) |
| D. gender assets_owner | 0.043* | 0.043* | 0.045* | 0.047* | 0.047* | 0.048* | -0.044 | -0.043 | -0.041 |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.049) | (0.049) | (0.049) |
| | D.Total consumption | | | D. Food consumption | | | D. Non-food consumption | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| D.Free medical services | 0.005 | 0.002 | 0.003 | 0.032 | 0.028 | 0.032 | -0.081 | -0.073 | -0.090* |
| | (0.026) | (0.027) | (0.026) | (0.025) | (0.026) | (0.025) | (0.052) | (0.053) | (0.053) |
| D.health_related_group | -0.062 | -0.062 | -0.066 | -0.078* | -0.077* | -0.081** | 0.094 | 0.088 | 0.080 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (0.045) | (0.045) | (0.045) | (0.040) | (0.040) | (0.040) | (0.082) | (0.082) | (0.083) |
| D.financial_ group | 0.085*** | 0.084*** | 0.084*** | 0.054** | 0.054** | 0.054** | 0.160*** | 0.158*** | 0.156*** |
| | (0.026) | (0.026) | (0.026) | (0.027) | (0.027) | (0.027) | (0.046) | (0.046) | (0.046) |
| D.received loan | 0.020 | 0.019 | 0.016 | 0.022 | 0.021 | 0.020 | 0.058 | 0.062 | 0.050 |
| | (0.051) | (0.051) | (0.052) | (0.045) | (0.045) | (0.045) | (0.091) | (0.091) | (0.092) |
| D.remittances | 0.065 | 0.068 | 0.064 | -0.024 | -0.022 | -0.026 | 0.210** | 0.214** | 0.209** |
| | (0.053) | (0.053) | (0.053) | (0.046) | (0.046) | (0.046) | (0.102) | (0.103) | (0.103) |
| Risk taker | 0.024 | 0.024 | 0.024 | 0.033** | 0.033** | 0.033** | 0.012 | 0.011 | 0.009 |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.016) | (0.035) | (0.034) | (0.035) |
| Risk neutral | 0.019 | 0.020 | 0.019 | 0.002 | 0.002 | 0.002 | 0.044** | 0.045** | 0.043** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.021) | (0.021) | (0.021) |
| Wave variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Community dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Head characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 | 3,105 |
| R-squared | 0.086 | 0.086 | 0.087 | 0.088 | 0.088 | 0.088 | 0.093 | 0.093 | 0.092 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1