

Forests, weather shocks and food security in developing countries

Jessica Meyer

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Forests, weather shocks and food security in developing countries

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Abstract

The doctoral thesis focuses on the interactions between forests, weather shocks and food and nutrition security in developing countries. The first chapter aims to reconcile questions pertaining to local communities' resilience to weather shocks, while using food security as the main indicator of household well-being, with questions linked to forests' role in households' ability to resist such shocks. Given the dual challenge of preserving access to forests for forest-dependent communities and reinforcing the sustainable use of natural resources, the second chapter of the dissertation investigates the impact of a forest co-management scheme in Malawi on both forest conservation and poverty alleviation. Finally, the third and last chapter places an emphasis on children's vulnerability to the effects of climate change and on women's role in mitigating these effects. Specifically, in light of the pivotal role women can play in the allocation of household resources, this analysis explores whether higher levels of women's empowerment can help mitigate the adverse impacts of high temperatures on children's nutritional well-being. The research themes addressed in this dissertation shed light on some of the major challenges experienced by developing countries, including high deforestation rates, elevated levels of food and nutrition insecurity, and an increase in the frequency, intensity, and duration of extreme weather events.

Keywords: Forests, Weather shocks, Food security, Nutrition, Resilience, Vulnerability, Safety nets, Forest co-management, Responses to shocks, Women's decision-making, Sub-Saharan Africa

Resumé

Mots-clés : Forêts, Chocs météorologiques, Sécurité alimentaire, Nutrition, Résilience, Vulnérabilité, Filets de sécurité, Cogestion des forêts, Réponses aux chocs, Pouvoir de décision chez les femmes, Afrique subsaharienne

La thèse porte sur les interactions entre les forêts, les chocs météorologiques et la sécurité alimentaire et nutritionnelle dans les pays en voie de développement. Le premier chapitre vise à évaluer la résilience des communautés locales face aux chocs météorologiques, en utilisant la sécurité alimentaire comme principal indicateur de bien-être, et en se focalisant sur le rôle des forêts comme filets de sécurité. Face au double défi de préserver l'accès aux forêts pour les communautés dépendantes de celles-ci et de renforcer l'utilisation durable des ressources forestières, le deuxième chapitre de la thèse examine l'impact d'un régime de cogestion des forêts au Malawi sur la conservation des forêts et la lutte contre la pauvreté. Enfin, le troisième chapitre met l'accent sur la vulnérabilité des enfants aux effets des chocs climatiques et sur le rôle des femmes dans l'atténuation de ces effets. Plus précisément, compte tenu du rôle central que les femmes peuvent jouer dans l'allocation des ressources au sein du ménage, cette analyse explore dans quelle mesure un pouvoir de décision plus important chez les femmes peut contribuer à atténuer les impacts néfastes des températures élevées sur le bien-être nutritionnel des enfants. Les thèmes de recherche abordés dans cette thèse soulignent certains des défis majeurs auxquels sont confrontés les pays en développement. Parmi ces défis figurent des forts taux de déforestation, des niveaux élevés d'insécurité alimentaire et nutritionnelle, ainsi que l'augmentation de la fréquence, de l'intensité et de la durée des événements météorologiques extrêmes.

Résumé détaillé

La thèse porte sur les interactions entre les forêts, les chocs météorologiques et la sécurité alimentaire et nutritionnelle dans les pays en voie de développement. Le premier chapitre vise à évaluer la résilience des communautés locales face aux chocs météorologiques, en utilisant la sécurité alimentaire comme principal indicateur de bien-être, et en se concentrant sur le rôle des forêts comme filets de sécurité. L'objectif est notamment d'explorer l'efficacité des forêts en tant que filet de sécurité pour la sécurité alimentaire en tenant compte d'autres stratégies disponibles pour la gestion des risques. Les résultats de cette analyse suggèrent que les forêts peuvent contribuer à atténuer les impacts négatifs d'un aléa climatique sur la diversité alimentaire des ménages, même en présence d'alternatives. Ainsi, les ressources forestières pourraient être mobilisées comme un filet de sécurité en cas de dernier recours ou en complément d'autres options, permettant, potentiellement, de limiter la nécessité de recourir à des stratégies d'adaptation coûteuses.

Face au double défi de préserver l'accès aux forêts pour les communautés dépendantes de celles-ci et de renforcer l'utilisation durable des ressources forestières, le deuxième chapitre de la thèse examine l'impact d'un régime de cogestion des forêts au Malawi sur la conservation des forêts et la lutte contre la pauvreté. Bien que la cogestion des ressources naturelles puisse concilier les besoins des populations avec ceux de l'environnement, nos résultats suggèrent que, dans le contexte du Malawi, elle a eu un effet négatif sur la vulnérabilité des communautés locales, du moins à court terme. Cet effet est plus marqué chez les ménages ayant peu d'options pour générer des revenus et dépendant fortement des ressources naturelles. En ce qui concerne les forêts, nous ne trouvons, dans l'ensemble, aucun effet de la cogestion sur le taux de déforestation.

Enfin, le troisième chapitre met en lumière la vulnérabilité des enfants aux effets des

chocs climatiques et explore le rôle des femmes dans l'atténuation de ces effets. Considérant le rôle essentiel que les femmes peuvent jouer dans la gestion des ressources familiales, cette analyse examine dans quelle mesure un renforcement du pouvoir de décision des femmes peut contribuer à atténuer les répercussions négatives des températures élevées sur le bien-être nutritionnel des enfants. Nos résultats empiriques confirment que les femmes disposant d'un plus grand pouvoir décisionnel peuvent jouer un rôle clé dans la protection de l'état nutritionnel des enfants après une exposition prolongée à la chaleur. Cet effet modérateur semble particulièrement accentué chez les enfants présentant les niveaux de nutrition les plus bas. Ces conclusions suggèrent que la capacité des femmes à prendre des décisions au sein du foyer est cruciale pour répondre aux défis de santé immédiats auxquels font face les enfants les plus vulnérables.

Les trois chapitres de la thèse adoptent des approches empiriques pour traiter les différentes problématiques de recherche. À cet égard, nous faisons appel à deux principaux types de données ménages. Dans les deux premiers chapitres, nous nous appuyons sur une enquête en panel représentative au niveau national pour le Malawi. Cette approche facilite notamment l'utilisation de méthodes empiriques capables de prendre en compte le biais résultant de variables omises qui restent constantes dans le temps. De plus, la disponibilité de coordonnées géographiques dans cette base de données permet d'intégrer des informations de télédétection au niveau de la zone d'énumération. Dans le cadre du premier chapitre, cela nous permet de relier de manière plus précise les chocs climatiques aux stratégies d'adaptation des ménages, potentiellement liées à l'utilisation des ressources forestières. Dans le deuxième chapitre, l'ajout d'informations spatiales permet de déterminer l'emplacement exact des réserves forestières par rapport aux ménages, ce qui rend possible une évaluation de la cogestion forestière au Malawi. Quant au dernier chapitre, il exploite une base de données combinant des informations à la fois au niveau individuel et au niveau des ménages à travers plusieurs pays d'Afrique subsaharienne, et sur plusieurs années. De plus, cette base de données inclut des informations sur les niveaux de température et de précipitations, nous permettant d'explorer les liens potentiels entre les chocs climatiques et le bien-être nutritionnel des enfants.

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List of Acronyms

CBA	Cost-Benefit Analysis
CEDA	Centre for Environmental Data Analysis
DHS	Demographic Health Surveys
DiD	Difference-in-differences
EA	Enumeration Area
FAO	Food and Agriculture Organization
FANTA	Food and Nutrition Technical Assistance Project
FCS	Food Consumption Score
FR	Forest Reserves
FVS	Food Variety Score
GDI	Gender Development Index
GHG	Greenhouse gas
GIS	Geographic Information Software
GPS	Global Positioning System
HDDS	Household Dietary Diversity Score
IHPS	Integrated Household Panel Surveys
IF	Influence Function
IFMSLP	Improved Forest Management for Sustainable Livelihoods Program
IPCC	Intergovernmental Panel on Climate Change
IPUMS	Integrated Public Use Microdata Series database
LSMS-ISA	Living Standards Measurement Study-Integrated Surveys on Agriculture
MEaSUREs	Making Earth System Data Records for Use in Research Environments

MWK	Malawian Kwacha
NASA	National Aeronautics and Space Administration
NTFPs	Non-Timber Forest Products
PET	Potential evapotranspiration
РНС	Population and Housing Census
PFM	Participatory Forest Management
PSM	Propensity Score Matching
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RIF	Recentered Influence Function
SADC	Southern African Development Community
SOFI	The State of Food Security and Nutrition in the World
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SSA	Sub-Saharan Africa
SWPER	Survey-based Women's emPowERment index
ТА	Traditional Authority
UQR	Unconditional Quantile Regression
VCF	Vegetation Continuous Fields
WFP	World Food Programme
WHZ	Weight-for-height
WHO	World Health Organization

General Introduction

General introduction

Background

Climate change: a threat to food security and nutrition

Climate change represents one of the most significant, if not the utmost, threats of our era. The onset of global warming is undeniably tied to human activities, primarily through the release of greenhouse gases (GHG). As highlighted by the Synthesis Report of the Intergovernmental Panel on Climate Change (IPCC)'s Sixth Assessment Report, between the period 2011-2020, global surface temperatures reached 1.1°C above pre-industrial levels (1850-1900). The escalation of GHG emissions, resulting from unequal and unsustainable energy practices, land use, and consumption and production patterns, has contributed to the rise in the frequency and intensity of weather extremes, such as heatwaves, floods, droughts and storms, with harmful impacts on the environment and people across the globe (IPCC, 2023). Since the 1990s, the number of adverse weather events has doubled, with an average of 213 weather extremes that have occurred each year between 1990 and 2016 (FAO, IFAD, UNICEF, WFP and WHO, 2018). Amongst the effects of extreme climatic events are declines in food security, with subsequent repercussions on nutrition, livelihoods, and well-being, especially for vulnerable population groups (FAO, IFAD, UNICEF, WFP and WHO, 2018).

As emphasized by The State of Food Security and Nutrition in the World (SOFI) 2018 report, variations in climate and weather are key contributors of global hunger and are amongst the primary drivers of severe food crises. Countries that are the most exposed to climatic variability and extremes were shown to experience higher levels of food insecurity (Holleman et al., 2020). Indeed, adverse climatic and weather events negatively impact all of the determinants of food security, including food availability, access, utilization and stability. Additionally, they enhance the

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"other underlying causes of malnutrition related to child care and feeding, health services and environmental health" (FAO, IFAD, UNICEF, WFP and WHO, 2018). More specifically, the 2018 SOFI report highlights that climatic variability and extremes can compromise food availability by affecting agricultural production, crop yields, and cropping patterns. Fluctuations in food prices induced by climatic variations frequently accompany declines in agricultural income, compromising food access, quantity, quality, and diversity of consumed food (FAO, IFAD, UNICEF, WFP and WHO, 2018). Additionally, as underlined in the report, weather anomalies' impacts on water and sanitation, and on factors such as childcare and breastfeeding, contribute to impairments in dietary quality and diversity, leading to increased health risks and diseases. These challenges pose a threat to food utilization and overall nutritional well-being.

Vulnerability of developing countries

Although GHG emissions that stem from the burning of fossil fuels predominately originate from industrialized and post-industrial nations, developing countries currently bear, and are expected to continue bearing, the most severe impacts of climate change (Mertz et al., 2009). The heightened vulnerability of these economies to climate change can be attributed to several factors. Firstly, given that many lower-income countries are in tropical and sub-tropical regions, they are already exposed to elevated temperatures that are sub-optimal for a range of economic activities (Millner and Dietz, 2015). Greater warming is likely to render conditions even less favorable (Mendelsohn and Schlesinger, 1999). Furthermore, a multitude of these countries, notably in Africa and Asia, naturally face high variability in rainfall, which frequently translates into periods of drought or excess precipitation (Ludwig et al., 2007, Millner and Dietz, 2015). These regions can also experience considerable intra- and inter-annual rainfall variations, as characterized by the monsoon in many tropical areas (Millner and Dietz, 2015). Changes in water availability induced by climate change can have severe consequences for economies and societal infrastructures that are sensitive to variations in rainfall patterns (Stern, 2007). When the monsoon failed in India in 2002, seasonal rainfall experienced a deficit of 19%, which led to sharp declines in agricultural output and a loss of more than 3% in the country's GDP (Challinor et al., 2006).

Another main cause of developing countries' vulnerability to the effects of climate change can be referred to as *sensitivity* (Millner and Dietz, 2015). The concept captures these regions' heavy reliance on climate-sensitive sectors, primarily agriculture, for both national income and employment (Mertz et al., 2009, Millner and Dietz, 2015). Finally, lower-income economies are often faced with limited capacity to adapt to the impacts of climate change due to a lack of financial assets, including savings and credit, technological capacity, infrastructure, effective governance, and access to information (Mertz et al., 2009, Millner and Dietz, 2015).

With these considerations in mind, Sub-Saharan Africa (SSA) stands out as the region the most vulnerable to the effects of climate change (Cuthbert et al., 2019), with close to 80% of its agricultural systems that are rain-fed (Gérardeaux et al., 2018, Sarr et al., 2021), and on which the majority of the population rely for livelihood (Challinor et al., 2007, Thompson et al., 2010, Kotir, 2011, Knox et al., 2012, Tesfaye et al., 2015). Moreover, the agriculture sector of the region is dominated by small-scale farms (typically smaller than 5 hectares), and is usually characterized by a minimal utilization of modern inputs and low commercialization levels (Jayne et al., 2022). The intensification of weather extremes, such as prolonged periods of dry and wet spells, and heat stress, therefore puts under threat the livelihoods of many smallholders. These rural communities form the backbone of the food system in SSA (FAO, IFAD, UNICEF, WFP and WHO, 2020), however, they are themselves challenged by high levels of food insecurity (Frelat et al., 2016), and poverty (Harris and Orr, 2014, Harris, 2019). These factors contribute considerably to their limited capacity to adapt to the effects of climate change.

Response to the effects of climate change

Given these constraints, a multitude of studies have explored how small-scale farmers in SSA adapt and cope with climatic variability and extremes. It is well documented that African farmers discern shifts in climate and in inter-annual and intra-season variability, while being aware of the impact of these occurrences on agriculture and their livelihoods (Girard et al., 2021). Overtime, rural households have hence developed diverse practices and strategies to deal with the numerous risks they are confronted to, including those associated with weather (Maddison, 2007, Thomas et al., 2007, Hassan and Nhemachena, 2008, Bryan et al., 2009, Mertz et al., 2009, Bezabih and Sarr, 2012, Silvestri et al., 2012, Kosmowski et al., 2016, Elum et al., 2017).

Such approaches can involve the adoption of coping strategies, which are typically characterized as independent, temporary and context-specific actions (Ashton, 2002, Turner et al., 2003, Ashraf and Routray, 2013) that can help alleviate the detrimental effects of climate variability and extremes in the short-term, without necessarily addressing the underlying or long-term risks associated to these events (Cooper et al., 2008, Alemayehu and Bewket, 2017). An example of a prevalent coping strategy in agricultural settings include the sale of assets. This could entail liquidating assets initially acquired for savings, such as smallstock, as well as considering the sale of more productive assets, such as cattle or land, especially in the face of severe shocks (Jodha, 1978, Corbett, 1988, Osbahr et al., 2008, Smucker and Wisner, 2008, Silvestri et al., 2012, Wunder et al., 2014b).

Households prone to shocks can also aim to adjust to the effects of climate change, whether already experienced or envisaged, through the adoption of adaptation strategies (Brooks, 2003, Smit and Wandel, 2006, Cooper et al., 2008, Osbahr et al., 2008). In contrast to coping mechanisms, adaptation measures are long-term plans that are anticipated, and generally continuous, designed to respond to changes in broader environmental conditions, instead of a specific shock

(Brooks, 2003, Gallopín, 2006). To effectively manage potential risks, households can, for instance, smooth income fluctuations *ex-ante* by opting to diversify their sources of livelihood (Dercon, 2002).

Nonetheless, as highlighted in Girard et al. (2021), there are some instances where the differentiation between coping (*ex-post*) and adaptation measures (*ex-ante*) can become unclear. Some coping mechanisms may persist over time and evolve into broader anticipatory measures, while others may necessitate preparation beforehand in order to effectively alleviate the effects of an adverse event. As an example, households in developing economies can insure themselves by building up assets during favorable times, foreseeing the potential need to deplete them at a later stage to cope with an unexpected shock (Dercon, 2002). Moreover, within the context of SSA, coping and adaptation mechanisms may form an integral part of communities' overarching livelihood strategies. Many of these measures are not solely adopted to address climate variability and extremes, but are also utilized to navigate and mitigate various risks and shocks (Girard et al., 2021).

Numerous studies that have examined smallholders' responses to adverse weather events have also highlighted the determinants that influence the type of adaptation and coping measures households choose to adopt, as well as the factors that limit their adaptive capacity. Amongst these considerations are market dynamics, which can encompass the access to insurance and credit (Maddison, 2007, Bryan et al., 2009, Deressa et al., 2009, Hisali et al., 2011, Silvestri et al., 2012), the conditions of local labor markets (Corbett, 1988), as well as the access to output and input markets (Hassan and Nhemachena, 2008). The socioeconomic attributes of households also significantly influence the selection and availability of coping and adaptation strategies. Some of these characteristics include wealth (Corbett, 1988, Bryan et al., 2009, Berman et al., 2015), risk aversion (Alderman and Paxson, 1994, Knight et al., 2003, Bezabih and Sarr, 2012), factor endowments and possession of assets (Deressa et al., 2009, 2010, Angelsen et al., 2014, Wunder et al., 2014b), as well as sources of livelihoods (Corbett, 1988), amongst other aspects, such as demographic features. Finally, adaptation strategies can be shaped by local geographic and biophysical factors, such as the proximity of forests (Hegde and Bull, 2008, Fisher et al., 2010) and natural resources (Bryan et al., 2013, Opiyo et al., 2015), agro-ecological zones (Deressa et al., 2009, 2010, Hisali et al., 2011, Bryan et al., 2013, Alemayehu and Bewket, 2017), aspects directly related to the adoption of the adaptation methods, such as cost (Bryan et al., 2013, Opiyo et al., 2015) and skills (Opiyo et al., 2015), as well as by other local conditions, including, but not limited to, distance to the nearest market or population center (Hisali et al., 2011, Silvestri et al., 2012, Angelsen et al., 2014, Noack et al., 2015).

Because of many constraining factors, rural households in developing countries will typically have a very limited portfolio of adaptation and coping strategies (Helgeson et al., 2013). Formal strategies will, notably, often be unavailable to them due to limited public services and a low penetration of market-based instruments, resulting, for instance, from a lack of finance institutions and collateral (Helgeson et al., 2013). Moreover, the effectiveness of informal insurance mechanisms, which depend on family and social networks, may diminish when the adverse event impacts a significant portion of individuals, as is often the case with weather-related shocks (Helgeson et al., 2013). Climatic conditions can also inherently constrain the range of coping and adaptation mechanisms accessible to households, by rendering them ineffective or impractical. Typically, self-insurance reliant on livestock accumulation may lose effectiveness in the event of a drought due to a heightened risk of livestock mortality (Dercon, 2002).

Contribution of the dissertation

The dissertation focuses on the interactions between forests, weather shocks and food security and nutrition in developing countries. The first chapter investigates the effectiveness of forests as a safety net in the aftermath of a weather shock, notably amidst other possible insurance options. The second chapter examines the potential success of forest co-management programs in reconciling the needs of communities and environmental preservation. Finally, the third chapter strives to offer additional evidence on differential levels of vulnerability across population subgroups, and on the contribution of women's empowerment in mitigating the effects of weather shocks on child nutrition.

In light of the various factors that determine households' capacity to cope with and adapt to the effects of climate change in developing countries, one of the general objectives of the dissertation is to contribute to the literature on the heterogeneous effects of shocks according to these determinants. The complex interplay of diverse socioeconomic, environmental, and institutional factors is, indeed, likely to lead to varying levels of resilience and adaptive capacities between groups of individuals. This household diversity is further examined within the context of a policy aimed at improving livelihoods through sustainable forest management. Specifically, the first chapter investigates disparities in households' resilience to weather shocks and their strategies for adaptation, considering specific aspects tied to local geography, biophysical conditions, asset ownership, and livelihood sources. Subsequently, the second chapter delves into the impacts of an intervention based on households' portfolio of labor activities. Finally, the third chapter explores how adverse weather events may affect households differently according to disparities in bargaining power and preferences between partners. Particularly, we analyze how various aspects of women's empowerment can shape responses to shocks and subsequent coping abilities.

The contribution of the thesis also lies in its central focus on food security and nutrition as primary indicators of well-being. While income is pivotal for meeting food needs and accessing other essential resources, examining food consumption patterns and nutritional outcomes enables a deeper understanding of households' direct consumption, while providing additional insights into the well-being of communities characterized by limited market access, informal activities, and heavy reliance on subsistence farming. Focusing on food security and nutrition could also

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facilitate the identification of shifts in well-being that stem from fluctuations in prices and subsequent declines in household purchasing power. Furthermore, by looking at such measures, we provide information on well-being from both input and output perspectives. Food security, that we measure through dietary diversity, informs on household access to a range of foods, and acts as an indirect indicator of nutrient adequacy in individual diets (Kennedy et al., 2011). Conversely, assessing an individual's nutritional status, through anthropometric indicators, offers valuable insights into the sufficiency of energy and nutrient intake, as well as the resulting health implications. Specifically, overconsumption of calories can lead to weight gain and increase the risk of developing various non-communicable diseases (Bhattacharya et al., 2019). On the other hand, an insufficient intake of energy and essential nutrients can lead to undernutrition, heightening the risk of disease and mortality due to reduced body immunity, especially amongst vulnerable populations (Kuruvilla et al., 2016, Maleta, 2006, Schofield and Ashworth, 1996). Considering nutritional outcomes in early stages of life, especially, is critical both from a health and economic perspective (Blom et al., 2022). Indeed, through its influence on cognitive development, nutrition is a key determinant of capital formation, and, consequently, of long-term economic development (Blom et al., 2022).

Finally, the dissertation broadens the evidence base on the relationship between forests and human welfare. This topic is of critical importance given that over 1 billion people worldwide derive direct and indirect benefits from forests in the form of employment and contributions of forest products to livelihoods and incomes (Angelsen and Wunder, 2003, Angelsen et al., 2014, Wunder et al., 2014a). In this context, the dissertation first focuses on aspects linked to forests' insurance properties, given evidence that they can serve as a form of natural insurance for households in the aftermath of a crisis (e.g., Pattanayak and Sills, 2001). Numerous elements contribute to the attractiveness of forests for households with limited resources and restricted access to formal insurance mechanisms. These include the diverse range of forest products often readily available for use and/or consumption (Wunder et al., 2014b), as well as the minimal capital investment and skills required for resource extraction, despite the potential labor intensity and physical demands involved (Wunder, 2001). The thesis specifically focuses on the effectiveness of forests as a safety net following a weather shock while using food security as the main indicator of household well-being. This approach, notably, allows to account for both of forests' market and non-market benefits. Subsequently, the dissertation delves into matters associated with forest access for adjacent communities and the sustainable use of forest resources though the evaluation of a forest co-management program. This question is crucial due to the substantial reliance on forest products globally and its potential implications for resource conservation.

Through its diverse research questions, the dissertation first permits to fill the literature gaps with respect to the protective role of natural capital for food security within the framework of a portfolio of potential safety net options. This question is especially relevant for policies focused on enhancing agricultural households' resilience to adverse weather events, and for initiatives that seek to reinforce the sustainable use of natural resources given their contributions to human welfare and livelihoods. In light of the latter policy implication, the thesis then aims to expand the evidence base on the extent to which the co-management of natural resources can succeed in balancing human and environmental needs, considering mixed results to date. The objective is also to deepen understanding of the mechanisms of effects, which, to our knowledge, have not yet been thoroughly explored empirically. This research hopes to shed light on the conditions under which policies that facilitate reliance on environmental income can enhance well-being while safeguarding forest environments. Lastly, through the final chapter, the dissertation contributes to the literature on women's role in adaptation and mitigation processes in developing countries. With respect to previous work, we shed light on how specific dimensions of women's empowerment might protect child nutrition following exposure to elevated temperatures across several countries and across time. Furthermore, we investigate how this role might vary according to the nutritional level of the child, which, as far as we are aware, also constitutes a novel contribution. Overall, this research holds implications for interventions that strive to address the unique needs and capacities of different population subgroups in efforts to build resilience to climate change.

The several themes covered in the dissertation call for the utilization of various types of data. Household surveys are mobilized across the three chapters of the thesis to obtain key information on respondents' demographic characteristics, socioeconomic status, employment, asset ownership, dietary habits, anthropometric measurements, and more. Specifically, in the first two chapters, nationally representative household panel surveys for Malawi are utilized, allowing to explore variations overtime for the same households. An important aspect of these surveys is the inclusion of Global Positioning System (GPS) coordinates at the enumeration area (EA) level, facilitating the integration of remote sensing data. In the first chapter, household data is coupled with a drought index and information on forest cover, enabling an examination of forests' role as a safety net in the aftermath of weather shocks. In the second chapter, information on the location of Forest Reserves and gross forest loss is integrated to assess the impact of forest co-management on both poverty alleviation and forest conservation. In the final chapter, we mobilize data from multiple rounds of household surveys conducted across several countries in Sub-Saharan Africa. The cross-sectional surveys employed in this context are particularly well-suited to study questions linked to child health, nutrition, and women's empowerment, amongst other topics.

Related literature, data and main results

Chapter 1

In light of the limited access of agricultural households to formal insurance mechanisms in developing countries and the potential ineffectiveness of informal social capital following a covariate shock, the first chapter of the dissertation assesses the extent to which natural capital can serve as a viable insurance alternative. Precisely, the analysis looks at the role of forests in households' ability to resist weather-related shocks while using food security as the main indicator of household well-being. The use of forests as a safety net is notably investigated with respect to other insurance mechanisms potentially available to households. The focus of this study is on Malawi, a country that faces significant vulnerability to climate change in large part due to its reliance on rain-fed agriculture as the cornerstone of its economy, employment, and food security (Giertz et al., 2015, Benson, 2021). Concurrently, in recent years, the country has been facing a rise in the frequency and intensity of weather-related shocks.

Previous work investigating the effectiveness of forest resources as an insurance option has frequently focused on income as the primary outcome measure (e.g., Noack et al., 2019). However, as underlined earlier, although income is vital for meeting basic needs and accessing essential resources, our analysis prioritizes food security as the primary indicator. This choice allows us to directly assess households' consumption patterns and gain further understanding of the well-being of communities characterized by limited market access, engagement in informal activities, and a strong dependence on subsistence farming. Mulungu and Manning (2023) provide empirical evidence on forests' ability to protect diets following a weather shock. With respect to this work, our study explores potential sources of heterogeneity by investigating the extent to which forests serve as an effective safety net for food security following a weather shock when considering the avail-

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ability (or lack thereof) of other risk-management options. The aim is to provide additional insights into the characteristics of households that rely on forests during challenging times, while shedding light on the role of forest resources within the framework of a portfolio of potential safety net options.

To conduct this analysis, we mobilize information on household level characteristics, such as food security, food expenditures, asset ownership, amongst other household features, from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). The LSMS-ISA study designs and establishes nationally representative panel household surveys in several SSA countries, with a heightened focus on agriculture. Within the framework of the first chapter, we specifically use the panel for Malawi across three rounds: 2010, 2013, and 2016. One of the advantages of this dataset is the availability of GPS coordinates for the sampled population, which makes it possible to overlay geospatial data at each EA. In this context, to measure households' exposure to dry and/or wet spells, we notably join to the household data the Standardized Precipitation Evapotranspiration Index (SPEI), introduced by Vicente-Serrano et al. (2010), from the high-resolution SPEI gridded dataset for Africa from the Centre for Environmental Data Analysis (CEDA) (Peng et al., 2019). Additionally, we overlay information on percentage tree cover derived from NASA's Vegetation Continuous Fields (VCF) data product, introduced by Hansen and Song (2018). Regarding the methodology, we exploit the panel dimension of the data and apply a linear model with household and year fixed effects. To test the effectiveness of forests as a safety net with respect to other insurance options, we explore how this role may vary according to household ownership of livestock and durable goods, as well as participation in ganyu labor.

The main results of this chapter first show that the occurrence of a weather shock during Malawi's rainy agricultural season negatively impacts household dietary diversity. However, the study reveals that forests can play an important role in mitigating these negative effects, in line with Mulungu and Manning (2023).

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Importantly, our results suggest that, in the majority of instances, forests serve not only as a reliable safety net for food security in the absence of other options, but may, potentially, also be a viable resource for Malawian households that own livestock, assets, or engage in *ganyu* labor. These findings emphasize the significance of preserving forest ecosystems for human welfare. Additionally, they highlight the need for interventions that aim at enhancing the resilience of agricultural systems, while preventing deforestation (Mulungu and Manning, 2023), and expanding households' portfolio of insurance options. Such measures would contribute to increasing overall adaptive capacities, especially amongst vulnerable population groups. Furthermore, the utilization of forests as a form of natural insurance raises concerns about potential overexploitation and environmental degradation (Delacote, 2007, 2009), highlighting the necessity for policy frameworks that balance human needs with environmental preservation goals.

Chapter 2

The central focus of the second chapter of the thesis relates to one of the important policy implications raised by the first chapter: how to preserve forest access for forest-dependent communities while ensuring the sustainable use of forest resources. As underlined earlier, the question of sustainable forest management is pivotal given the significant dependence on forest products worldwide, and its potential consequences on resource conservation. This reliance on forest resources for meeting essential needs such as nutrition, energy, and housing, has spurred governments and other stakeholders to develop and implement policies aimed at supporting livelihoods, alleviating poverty, and conserving natural resources (Shyamsundar et al., 2020). An example of a widely adopted policy since the 1990s is the co-management of natural resources, which typically involves the devolution and transfer of rights to access, use and manage common-pool resources from governments to communities, often times formalizing aspects of pre-existing *de facto*
common property regimes (Ostrom, 1990, Baland and Platteau, 1996, Engel et al., 2013, Mansuri and Rao, 2013). In practice, co-management also frequently encompasses the implementation of activities designed to enhance the well-being of communities and improve returns to labor for households engaged in resource extraction and production.

Thus far, an important portion of the available evidence on the impact of forest co-management on poverty alleviation and conservation has been derived from case studies, small sample sizes, or surveys conducted in geographically restricted areas (Hajjar et al., 2021, Miller et al., 2021). The few studies that have adopted a program evaluation approach estimate, in most instances, either poverty or forest outcomes, and provide little empirical evidence on the behavioral pathways through which co-management affects poverty and forests, as well as on the mechanisms through which these schemes influence behavior underlying outcomes. Overall, previous research conducted at the household level suggest mixed effects when it comes to the impact of co-management on poverty and/or forest conservation, including in SSA, as well as heterogeneous effects within co-management schemes. Hence, this analysis contributes to expanding the evidence base and deepening our understanding of the factors influencing the outcomes of co-management by examining both poverty and forest-related outcomes. This is accomplished through a program evaluation of the Improved Forest Management for Sustainable Livelihoods Programme (IFMSLP), a national-level forest co-management initiative in Malawi.

Similar to the first chapter, the second chapter of the thesis mobilizes the World Bank's LSMS-ISA for Malawi, while taking advantage of the availability of a fourth wave of data for the year 2019. As a result, the household data employed constitutes a four-year panel spanning the years 2010, 2013, 2016, and 2019. To investigate the influence of co-management on the condition of forests, we construct a measure of gross forest loss using the Global Forest Change dataset by Hansen et al. (2013). We also use shapefiles of Malawi's Forest Reserves, which allow us

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to make a clear distinction between forests under co-management and forests not under co-management. To infer a causal relationship between co-management and its impacts on poverty and deforestation, we generate a counterfactual from a control group comprised of households that live in communities located within a certain distance of Reserves that were not selected into the program. Our primary empirical strategy hence consists in a difference-in-differences (DiD) approach that we combine with a Propensity Score Matching (PSM). This methodology allows us to establish comparability between our treated and untreated groups using PSM and to address unobserved characteristics through DiD.

The results from the application of the DiD framework suggest that the IFMSLP increased rather than reduced household poverty, at least in the short-term. This heightened vulnerability is particularly observed amongst households with limited labor alternatives and a reliance on resource extraction and/or agricultural production. Regarding forests, the overall analysis indicates no clear treatment effect on gross deforestation rates. However, a closer examination of regional disparities uncovers a potential rise in forest loss in the Central region, where the increase in poverty levels also appears to be concentrated. At this stage, these findings underscore the importance of ensuring that communities targeted by policies centered on natural resource extraction and utilization have access to alternative incomegenerating activities. Additionally, while transferring access and withdrawal rights to communities may benefit households utilizing resources, transferring management and exclusion rights could increase extraction costs. Careful consideration of the configuration of forest rights prior to the implementation of co-management initiatives hence appears crucial, as it is likely to influence these additional costs or benefits.

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Chapter 3

In its third chapter, the dissertation aims to provide further insights into households' varying vulnerability to extreme weather-related events based on householdlevel dynamics. Specifically, we examine the effects of increased temperatures on the nutritional status of children under five, while also considering how differences in bargaining power between partners may influence susceptibility to child undernutrition following such events. To account for these differences, we employ an indicator of women's empowerment, known as the SWPER (Ewerling et al., 2017), which encompasses various dimensions of empowerment including decision-making, intolerance to violence, and social independence.

Previous work has shed light on the influence of maternal education in protecting child nutrition in the event of climate-related shocks. Dimitrova and Muttarak (2020) notably show that children born into economically disadvantaged households, but with educated mothers, encounter nearly identical risks of stunting as a result of a weather shock as children born into more affluent households, but to mothers who lack education. Additionally, their findings reveal that the main pathways through which mother's education leads to improved health outcomes for her children include enhanced health knowledge and increased utilization of healthcare. Female empowerment was found to have a lesser influence. With respect to this work, our research seeks to elucidate how specific aspects of empowerment contribute to improved child nutrition outcomes in the face of weather anomalies. In light of the important role women can play in the allocation of household resources, we primarily focus on mother's level of decision-making. To support this choice, we notably propose a simple model of equality between partners and child nutrition which demonstrates that, in a household where the mother has an increased preference for child nutrition compared to her partner, the allocation of resources to child nutrition will experience a more substantial rise following an income shock when the mother possesses greater bargaining power.

With respect to data, we employ the Integrated Public Use Microdata Series database (IPUMS-DHS) to extract key information on child nutrition, women's empowerment, alongside other household and individual-level characteristics, as well as on weather variability. IPUMS-DHS harmonizes Demographic and Health surveys (DHS), which are widely used nationally-representative surveys on population, health, and nutrition, facilitating analyses across different countries and across time. Hence, the final dataset combines a series of DHS surveys from 25 African countries, over the period 2000-2019. These surveys are derived from the DHS children record, with children under five serving as the unit of analysis. The data is collected through interviews with women of reproductive age (15 to 49 years old), who provide information about themselves, their children, and other household members. Additionally, IPUMS-DHS utilizes georeferenced information from DHS's GPS datasets to provide contextual variables such as temperature and precipitation. Regarding the empirical strategy, we adopt two methods. Firstly, to estimate the impact of elevated temperatures on child nutrition and the potential moderating influence of women's empowerment, we employ a linear regression model with regional fixed effects. Secondly, to explore potential variations in our results based on the child's nutrition level, we employ unconditional quantile regressions (UQR), popularized by Firpo et al. (2009). This methodology enables us to assess the impact of explanatory variables on various quantiles of the outcome.

Our findings highlight the significant role of women with greater decisionmaking power in preventing acute malnutrition in children during periods of extreme heat. With respect to Dimitrova and Muttarak (2020)'s findings, these results suggest that, for a given level of education, active participation in household decision-making is a crucial factor influencing women's role in adaptation and mitigation processes. Secondly, results from UQR reveal that the role of women's empowerment as a moderating factor is especially pronounced for children with the lowest nutrition levels. These results suggest that improving women's instrumental agency can play a key role in the the reallocation of scarce household resources towards the well-being of children, especially within households particularly susceptible to hardship. Therefore, our findings imply that, alongside prioritizing various determinants of child nutrition such as agriculture, livelihoods, and health (Wheeler and Von Braun, 2013), efforts and initiatives aimed at mitigating the effects of climate change should also focus on empowering women and addressing gender inequality.

Chapter 1

How Do Forests Contribute to Food Security Following a Weather Shock? Evidence from Malawi

This work was published in *World Development* in 2023, under the following reference: Meyer, J. (2023). How do forests contribute to food security following a weather shock? Evidence from Malawi. Earlier versions of this work were presented at the following conferences and seminars: the Climate Economics Chair of Paris Dauphine internal seminar (2021); INRAE-AgroParisTech internal seminar (2021); UPEC-Erudite internal seminar (2022); the Journées Doctorales du Développement (JDD, 2022); the 10th Annual Conference of the IAERE (2022); the 27th Annual Conference of the EAERE (2022); as well as at the 10th Annual Conference of the FAERE (2022). Thank you to the participants for their valuable comments.

Abstract

Rural residents in developing countries are particularly vulnerable to shocks related to weather events. In this context, forests are frequently presented as safety nets, especially for households with limited risk-management options. This analysis aims to provide further evidence on the effectiveness of such safety nets. Specifically, the objective of this work is to analyze the extent to which forests serve as an effective safety net for food security when other potential risk-management options are available, or not, in rural areas. Focusing on agricultural households in Malawi, we combine several rounds of observations from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) with geospatial data on forest cover and a drought index based on both precipitation and temperature. Our results show that forests play an important role in protecting households' diets in the aftermath of a weather shock, especially amongst those who appear to have limited insurance options, and/or who may need to further diversify their portfolio of potential insurance mechanisms to cope with a shock. By looking at food security, we highlight both the market and non-market benefits of forest resources in the aftermath of a shock. Moreover, we provide additional empirical evidence on the characteristics of households that depend on forest resources during challenging times. Overall, in light of the fundamental role forests play for human and planetary health, these findings shed light on the need to preserve forest access to forest-dependent communities and strengthen the sustainable management of forest resources.

1.1 Introduction

Changes in global climate are resulting in the increase in the prevalence, intensity, and severity of extreme weather events with important implications for agriculture and food security in the world's most vulnerable regions (IPCC, 2022). Indeed, weather shocks, such as floods, heat waves, and droughts, can induce crop yield loss, amongst other agricultural shortfalls, and negatively impact food availability, accessibility, utilization, and stability (FAO, IFAD, UNICEF, WFP and WHO, 2018). According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), about 3.3 to 3.6 billion people "live in contexts that are highly vulnerable to climate change". Such contexts include tropical and subtropical low-income countries that are already struggling with food insecurity (Thornton et al., 2014), low resilience, and where livelihoods, to a large extent, depend on climate-sensitive natural resources such as "agriculture, fisheries and forestry" (UN DESA, 2016).

Local communities can adopt several strategies to limit their exposure and vulnerability to risks and shocks (Girard et al., 2021). In market-remote areas, there is evidence that social and local natural capital can represent an accessible and affordable risk-coping strategy as opposed to "more technical and capital-intensive strategies, such as insurance" (Tibesigwa et al., 2016). In the face of covariate shocks, increasing attention has been paid to forest resources' ability to provide a form of natural insurance in developing countries' agricultural settings (Angelsen and Wunder, 2003).

Mindful of the increase in adverse weather conditions, consistent levels of malnutrition, and alarming deforestation rates in many developing countries, this study aims to explore the effectiveness of forests as a safety net for food security relative to other potential risk-management options that could be adopted by households following an adverse weather event. The case study is Malawi, which is particularly vulnerable to the effects of climate change primarily because of its heavy dependence on rain-fed agriculture for its economy, employment, and food needs (Giertz et al., 2015, Benson, 2021). Meanwhile, the frequency and intensity of weather shocks are rising in the country. In the 2014/2015 and 2015/2016 growing seasons, Malawi was hit by severe wet and dry spells (McCarthy et al., 2021), and most recently, in 2019, it experienced important flooding due to the Mozambican channel's tropical storm, severely impacting livelihoods and infrastructures (GoM (Government of Malawi), 2019). In addition, a large share of the Malawian population directly depends on natural resources for "food, fuel, and maintenance of livelihoods" (Johnson et al., 2013).

Amongst the literature that has focused on forests' insurance properties, there are, on one hand, analyses that look at whether forests are used as a safety net by smallholders following an agricultural shock, such as the work by Pattanayak and Sills (2001). Indeed, the authors find that rural households are more likely to take forest collection trips following agriculture-related risks in the Brazilian Amazon. On the other hand, there are papers that investigate whether forests represent an effective safety net, such as Noack et al. (2019), that show that the income derived from the extraction of forest resources can offset the negative impacts of a drought on crop revenue. However, evidence on this last aspect, that is, the outcome of using forest resources as an insurance option, remains sparse and mainly focuses on income as an outcome indicator.

While income is crucial for meeting food needs and maintaining access to other critical resources, we utilize food security as a main outcome to capture households' direct consumption and attempt to provide some additional information on the well-being of communities that are characterized by limited market access, informal activities and heavy reliance on subsistence farming. Furthermore, looking at food security will permit to account for both forests' market and non-market benefits, which may not be captured by income data alone.

To our knowledge, only the work by Mulungu and Manning (2023), which also

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focuses on Malawi, provides evidence on forests' ability to protect diets following a weather shock. The authors demonstrate that agricultural households with access to common property forest products following an agricultural deficit experience a lower reduction in their dietary diversity. However, there exist important differences between households when it comes to vulnerability and adaptation to risks and shocks that are not considered in the aforementioned study. In a country like Malawi, whose population is primarily dependent on climate-sensitive natural resources, these discrepancies may lie in the options communities have at hand to cope with adverse weather events. These options may take the form of assets, labor, as well as access to credit, amongst other alternatives. In this paper, we therefore look into such sources of heterogeneity by testing to what extent do forests represent an effective safety net for food security following a weather shock when other risk-management options are accessible (or not) to agricultural households.

This analysis is important as it aims to offer further insights into some of the characteristics of households that most depend on forests during challenging times. It also sheds light on the role of forest resources within the framework of a portfolio of potential safety net options. Furthermore, in addition to accounting for the impact of either a wet or dry shock, we also look at the role of forests as a safety net for food security while differentiating between both types of adverse weather events. Moreover, we test for different shock severity levels. Overall, our results provide empirical evidence on forests' ability to offset negative impacts of a weather shock on agricultural households' diets, especially amongst those who appear to have limited insurance options, and/or who may need to further diversity their portfolio of potential insurance mechanisms to cope with a shock. To conduct this analysis, we mobilize the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Malawi across three survey rounds, to which we overlay remote sensing data on percentage forest cover, as well as the Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010).

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The paper is organized as follows: Section 1.2 provides elements on the several strands of literature this research contributes to; Section 1.3 describes the data mobilized, as well as the empirical strategy used; Section 1.4 presents the results of the analysis; and Section 1.5 discusses the findings and concludes.

1.2 Literature review

1.2.1 Weather shocks: a threat to food security and livelihoods

Greater weather variability and the occurrence of extreme meteorological events represent severe threats to food and nutrition security, especially in countries already suffering from hunger and malnutrition (Wheeler and Von Braun, 2013). Sub-Saharan Africa is particularly vulnerable to the increase in the prevalence, intensity, and duration of weather incidences (Tirado et al., 2015). Such events can have disastrous impacts on a region that highly depends on rain-fed agriculture¹ (Tirado et al., 2015), and where the coping and adaptive capacity is low due to market and institutional failures (Haile et al., 2018), widespread poverty, and disasters and conflicts, among other stressors (Tirado et al., 2015).

The populations most at risk of climate change and weather extremes are "smallscale farmers, herders, fishers and forest-dependent communities, who derive their food and income from renewable natural resources" (FAO, IFAD, UNICEF, WFP and WHO, 2018). These communities are also amongst the most nutritionally insecure (Kotir, 2011). Indeed, in addition to reducing food availability through decreased agricultural productivity, resulting in drops in food production and rises in food imports, weather shocks also have negative consequences on the other dimensions of food security, including food accessibility, food utilization and safety, as well as stability (FAO, IFAD, UNICEF, WFP and WHO, 2018).

According to the 2018 report of the State of Food Security and Nutrition in the

¹96 percent of Sub-Saharan Africa's cultivated land is rain-fed (FAO & IIASA, 2007).

World (SOFI), adverse climatic and weather events are a major cause of increases in food prices and revenue loss amongst agriculture-dependent populations, compromising people's access to food. Moreover, the report highlights that food utilization and safety are also undermined by climate variability and weather extremes as alterations in temperature and rainfall patterns can lead to the contamination of crops and "outbreaks of pests and diseases", which in turn threatens food safety and the consumption of diverse and nutritious foods. Detriments to these aspects of food security subsequently hinders the overall stability of food supply (FAO, IFAD, UNICEF, WFP and WHO, 2018).

1.2.2 Households' strategies to cope with risks and shocks

In developing countries' agricultural settings, the life of asset-poor communities is often characterized by insecurity and vulnerability to hardship (Shackleton et al., 2001, Paumgarten, 2005). These circumstances push smallholders to adopt a variety of livelihood strategies, which can be defined as the "capabilities, assets and activities required for a means of living" (Ashley et al., 1999). Such strategies reduce rural households' vulnerability to crises by providing them with a series of possible insurance alternatives and coping mechanisms (Paumgarten, 2005). By doing so, they can support agricultural populations in achieving a sustainable livelihood, which can be defined as one that "can recover from shocks and maintain and improve its assets without unsustainably impacting the available natural resource base" (Paumgarten, 2005).

The strategies adopted by local communities to adapt to and cope with weatherrelated shocks therefore comprise a central aspect of vulnerability (Adger and Winkels, 2014). They commonly either take place prior to the shock (*ex-ante*), in order to manage the risk, or as a response to it (*ex-post*), in order to cope with the risk (Wunder et al., 2014b, Girard et al., 2021). *Ex-ante* strategies can include practices aimed at buffering future shocks, through the accumulation of assets for instance (Wunder et al., 2014b), and the diversification of sources of livelihood (Girard et al., 2021), while *ex-post* responses can consist of actions that seek to smooth income and consumption, sell assets, or reallocate or increase labor (Alderman and Paxson, 1994, Dercon, 2002, Wunder et al., 2014b). We therefore investigate forests' safety net use relative to such strategies, including livestock and durable asset possession, as well as participation in a form of informal off-labor.

Because of limited public services and other institutional and market failures in developing countries' rural areas (Dercon, 2002), formal strategies, that are market-based or provided by the state, are often not available for rural households in low-income countries (Helgeson et al., 2013). Informal social and natural capital are, therefore, often central in strengthening the adaptive capacity of the most vulnerable households and in limiting their exposure and sensitivity to risks (Tibesigwa et al., 2016).

However, with regard to social capital, some studies highlight that, in the event of an adverse weather event, which is a covariate shock that impacts "many households in the same geographical location" (Pradhan and Mukherjee, 2018), informal safety net mechanisms that depend on the assistance of neighbors, family or friends may not provide viable relief as they could also suffer from the same shock (Wunder et al., 2014b). Yet, as underlined in Pisor and Jones (2021), amongst others, social capital could remain an effective strategy to cope with covariate shocks if social relationships are long-distance. Indeed, in settings where the topography is variable, there is likely to be a variety of resources across space (Halstead and O'Shea, 1982). Additionally, resources may be available at different times (Harpending and Davis, 1977). As such, in the event of a covariate shock, communities at a certain distance from each other may still have resources at hand to provide help to one another (Pisor and Jones, 2021).

On the other hand, natural capital, such as forest resources, can provide shockstricken households with additional and flexible alternatives following a crisis by offering a form of natural insurance, an attribute underlined early on in Pattanayak and Sills (2001). In areas particularly hit by poverty, the services provided by forests, especially non-timber forest products (NTFPs), can be central for food as well as for medicinal purposes, while often being freely accessible and harvestable, even for people with no land (Wunder et al., 2014b). Indeed, while the harvest of forest products is labor intensive and physically demanding (Wunder, 2001), it does not call for a lot of capital investment, nor skill, and is thus seen as particularly attractive for individuals with limited resources (Angelsen and Wunder, 2003, Paumgarten, 2005).

However, forests' ability to provide an effective safety net depends on the level of pressure their resources are subject to. If all individuals turn to the forest as a result of a covariate shock, forests' insurance properties are likely to be undermined due to over-harvest and resource depletion. As highlighted in Newton et al. (2016), a "greater reliance on (often diminishing) forest resources by growing numbers of people could generate unsustainable conservation".

1.2.3 Forests' benefits to diets and role as a natural insurance

Several studies have focused on forests' abilities to provide a form of insurance for rural communities in developing countries. Amongst these analyses, there are, on one hand, those that have looked at whether forests are used as an insurance option, such as the paper by Pattanayak and Sills (2001), which finds that rural households are more likely to take forest collection trips following agriculturerelated risks in the Brazilian Amazon. Baland and Francois (2005) also show that common pool resources can represent a risk-management tool for low-skilled individuals, which, as opposed to private projects, often calls for low-skilled labor.

On the other hand, there are also a few papers that have focused on the outcome, by empirically testing whether forests represent an effective safety net. Noack et al. (2019), for instance, show that the income derived from the extraction of forest resources can offset the negative impacts of a drought on crop revenue in several developing countries. Most recently, Andrews and Mulder (2022) also explore the contribution of forest income in households' ability to cope with shocks in Tanzania.

The question related to the role of forest resources as an insurance mechanism in comparison to other risk-management options has also been the focus of previous literature. McSweeney (2004), whose analysis takes place in the context of Eastern Honduras, shows that households that sell forest products as an insurance against shocks are generally poorer than others. Precisely, the paper highlights that households that relied on forest product sale in the wake of an adverse event possessed less land and lived in dwellings of lower quality. Moreover, Andrews and Mulder (2022) also look at the extent to which the insurance offered by forests varies by the availability of alternative risk-management options. In contrast to McSweeney (2004), and to other previous work such as that of Fisher (2004), the authors find that forests offer little insurance against shocks, particularly amongst the most vulnerable households. Their results, on the contrary, suggest that households that have access to a greater number of insurance options, including social capital, access to financial services (i.e., credit), and market integration, are more likely to turn to forests following a market-related shock. According to the authors, because the poorest households are already heavily dependent on forest resources, their reliance on these resources cannot further increase, even after a shock.

In line with these previous works, our study aims to provide further evidence on the extent to which forests offer a buffer against shocks when other risk-management options are considered. While McSweeney (2004) and Andrews and Mulder (2022) focus on the factors moderating households' reliance on forests following a shock, our study attempts to shed light on the importance of forests as an insurance mechanism relative to other possible alternatives. Precisely, we test whether forests continue to serve as an effective safety net for food security in the aftermath of a shock when other potential options are available to households, including livestock, durable assets, and participation in informal off-farm labor. Doing so could also allow to identify whether some of these options moderate households' reliance on forests.

While income, which has often been used in the literature on forests' natural insurance properties, is crucial for meeting food needs and maintaining access to other critical resources, we utilize food security as a main outcome to capture households' direct consumption and attempt to provide some additional information on the well-being of communities that are characterized by limited market access, informal activities and heavy reliance on subsistence farming. Furthermore, looking at food security will allow to account for both forests' market and nonmarket benefits, which may not be captured by income data alone.

To our knowledge, the work by Mulungu and Manning (2023) is the first to empirically explore the role of forests in protecting diets following weather shocks in rural Malawi. The authors find that the collection of NTFPs is positively correlated with a weather shock, and provide evidence that, in the face of agricultural shortfalls, agricultural households that could access common property forest products experienced a lower reduction in their dietary diversity. These findings are in line with the growing body of literature that focuses on the potential of forest products and services to positively influence diets.

Indeed, forest environments can improve dietary diversity through several channels, as represented in Figure 1.1. Amongst these properties, some can turn out to be particularly crucial in the face of adversity. Indeed, forest environments can render adequate food available for consumption in times of food shortages, including animal protein and fat, derived from vertebrates and invertebrates, fruits, nuts, tubers, leafy vegetables, and other plants that provide essential minerals and vitamins (Johns et al., 2006). Forest resources can also provide a source of complementary income through the sale of NTFPs and represent a significant gap-filling or safety net mechanism² (Angelsen and Wunder, 2003, Paumgarten, 2005). Ad-

²According to Paumgarten (2005), NTFPs constitute 'gap-filling' when they are collected by rural households for anticipated shortfalls with the aim of enhancing household food security and revenue. On the other hand, they can provide a 'safety net' as a result of unanticipated shocks, including natural disasters or illness for instance, by allowing households to access forest products rapidly and easily for direct consumption or sale.

ditionally, the variety of products and services provided by forests can comprise an essential component of rural communities' livelihood strategies, enabling them to decrease their vulnerability to shocks (Neumann and Hirsch, 2000), and hence, limit damages to food security and nutrition.



Figure 1.1: Causal pathways between forest cover and dietary diversity

Notes: Conceptual framework derived from Rasolofoson et al. (2018). In the figure, mother's time refers to the idea that living in proximity to forests renders fuelwood for cooking more readily available, allowing women to allocate more time to caring and cooking for their children as opposed to collecting fuelwood (McGuire and Popkin, 1989, Brown et al., 2014, Jagger and Shively, 2014, Galway et al., 2018).

In Malawi, NTFPs notably comprise insects, termites, caterpillars, bushmeat, honey, mushrooms, fodder, wild fruits and vegetables (amongst other edible plants), fibers, as well as firewood, thatch grass, and bamboo (EC-FAO, 1998, Mahonya et al., 2019). Some of these products are especially predominant during certain seasons. Termites, for instance, which provide an important source of protein, are generally caught at the onset of the rainy agricultural season (EC-FAO, 1998). Similarly, mushrooms, which also offer an important source of complementary food, are mostly available during the rainy season (Chipompha, 1985, EC-FAO, 1998). In addition to being used for own consumption, NTFPs, as described, also serve for

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income generation. The variety of indigenous fruits available in Malawi's forests, which are primarily closed and deciduous, and familiarly known as *miombo* (Fisher et al., 2010), can be made into juices and other products, and then sold in exchange for cash or barter (Maghembe and Seyani, 1991, Clarke et al., 1996). Mushrooms have also been reported to be sold by women and children at the side of roads (Clarke et al., 1996).

Furthermore, it is important to underline that forests can also directly influence local climates through biogeophysical processes, namely evapotranspiration and albedo (Snyder et al., 2004). Indeed, forests have a low albedo, which "contributes to planetary warming through increased solar heating of land", and via evapotranspiration, they have a climate cooling effect trough "feedbacks with clouds and precipitation" (Bonan, 2008). In the case of tropical forests, their strong evaporative cooling offsets surface warming associated with low albedo (Bonan, 2008). As highlighted in Bala et al. (2007), when considering the net effect of these processes, forests' evaporative cooling and carbon sequestration is likely to contribute to climate change mitigation.

As such, forests can help moderate droughts and floods. Indeed, by contributing to atmospheric moisture through evapotranspiration, moisture that is then transported by wind, forests promote water redistribution across terrestrial surface, and hence limit the occurrence of droughts (Brack, 2019). Moreover, by intercepting droplets from fog and clouds, and in so doing regulating water supplies³, forests also contribute to soil's capacity to infiltrate and retain water, allowing to mitigate flooding (Brack, 2019).

Our study thus contributes to the empirical evidence on the role of forests as a natural insurance for food security in the aftermath of a weather shock by investigating the following research question: *What is the role of forests as a safety net for food security relative to other risk-management options available (or not) to agricultural households following a weather shock?*

³Especially in the case of forests located in high altitudes (Brack, 2019).

1.3 Data and empirical strategy

1.3.1 Study area

Malawi is a prime example of a Sub-Saharan African country that is particularly challenged by climatic and weather variability. With most of Malawi's agricultural output being derived from smallholder rain-fed croplands, weather anomalies, such as wet and dry spells, highly impact the country's economic outcomes, exports of farm goods, as well as nutrition and food security (FAO, 2010, Pauw et al., 2010, Ministry of Agriculture and Food Security, 2011, Giertz et al., 2015, Warnatzsch and Reay, 2019). Moreover, with 50.7 percent of Malawians living below the poverty line, including 25 percent characterized as extremely poor, Malawi comprises one of the poorest countries in the world (IMF, 2017). Furthermore, 20 percent were found to suffer from undernourishment, amongst other health hazards, including HIV/AIDS, tuberculosis, anemia and malaria (FAO, IFAD & WFP, 2015).

Smallholders, who comprise 80 percent of the population in Malawi, according to the USAID, are especially vulnerable to extreme weather events, such as the recent floods and drought that respectively took place during the 2014/2015 and 2015/2016 growing seasons (McCarthy et al., 2021), and the severe flooding that occurred in 2019 following the Mozambican channel's tropical storm (GoM (Government of Malawi), 2019). The circumstances in rural areas, including the 41 percent poverty rate (World Bank, 2016) and the heavy dependence on climatesensitive agriculture, make it difficult for smallholders to adapt and cope with shocks and sustainably improve their nutritional outcomes (McCarthy et al., 2021). Meanwhile, tackling food insecurity and nutritional deficiencies is essential for a country's economic development as well as for human health and performance (Doctor and Nkhana-Salimu, 2017). Furthermore, Malawi also represents a pertinent case study for this research considering that a large share of its population directly depends on natural resources, notably forests, for "food, fuel, and maintenance of livelihoods" (Johnson et al., 2013). At the same time, Malawi's forests are subject to important pressures, including agriculture expansion, and, as cited in Ngwira and Watanabe (2019), overuse and extraction of biomass "such as wood, charcoal, and agricultural residues mainly used for cooking and heating" (Gowela and Masamba, 2002). These stressors are considered responsible for the significant reduction in forest cover from 47 to 36 percent that took place between 1975 and 2005, accounting for an estimated loss of 30,000 to 40,000 hectares per year and representing the highest rate of deforestation in the Southern African Development Community (SADC) region during this period (Mauambeta et al., 2010). Furthermore, based on recent estimates from the Global Forest Watch (2022), the country lost 193kha of its forest cover between 2001 and 2020, representing a 13 percent tree cover decline since 2000⁴.

1.3.2 Data

1.3.2.1 Household data

Information on household level characteristics, including households' socioeconomic status, food consumption, and agricultural and non-agricultural activities, is derived from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). The LSMS-ISA study designs and establishes nationally representative panel household surveys in several Sub-Saharan countries, with a heightened focus on agriculture. Within the framework of this research, we specifically use the Integrated Household Panel Surveys (IHPS) for Malawi across three survey rounds: 2010, 2013, and 2016. The household sample expanded each survey round via the tracking of both original and split-off house-

⁴These Global Forest Watch estimates do not account for forest cover gain.

holds (see Appendix A.1 for more information on split-off households). Hence, the panel sample, which comprised 1,619 households during the first survey round, enlarged to 2,508 households in the third (2016) round of the IHPS. Additionally, the LSMS-ISA panel surveys for Malawi are characterized by a low household level attrition rate. The attrition rate was 4 percent in the second survey wave (2013), as well as in the third wave (2016) (Moylan and Kilic, 2017). Moreover, thanks to the availability of GPS coordinates⁵ for the sampled population, it is possible to overlay geospatial data at each household enumeration area (EA) using Geographic Information Software (GIS). There are a total of 102 EAs.

1.3.2.2 Weather shocks

Furthermore, in order to measure households' exposure to both dry and wet weather shocks, we exploit the Standardized Precipitation Evapotranspiration Index (SPEI), introduced by (Vicente-Serrano et al., 2010), from the high-resolution SPEI gridded dataset for Africa from the Centre for Environmental Data Analysis (CEDA) (Peng et al., 2019). This dataset provides the SPEI index for the whole African continent over the period 1981-2016, at a spatial resolution of 0.05 degrees. Unlike the widely used Standardized Precipitation Index (SPI), the SPEI accounts for both precipitation and potential evapotranspiration (PET), allowing to capture "the main impact of increased temperatures on water demand" (National Center for Atmospheric Research (NCAR), nd). Specifically, the SPEI index reflects monthly deviations in water balance from the local historical average, with positive values corresponding to wet events and negative values to dry events (Vicente-Serrano et al., 2010). Moreover, the values are normalized in such a way that the average value of the index equals 0 and the standard deviation to 1 (Vicente-Serrano et al.,

⁵For questions of confidentiality, the GPS coordinates are randomly displaced by the LSMS-ISA team within a predetermined range, corresponding to 0-2km for urban areas and 0-5km for rural areas, where the risk of disclosure is greater due to more important community dispersion (Malawi National Statistical Office (MNSO), 2012). Additionally, 1 percent of rural clusters were attributed a 0-10km offset leading to an increase in the known range to 10km for all rural points (Malawi National Statistical Office (MNSO), 2012).

2010).

Additionally, similarly to the SPI, the SPEI index can be computed at different timescales ranging from 1 month to 48 months, allowing to differentiate between drought types (Vicente-Serrano et al., 2010). To measure the level of water balance for the periods that are pertinent for agriculture in Malawi, we use the 6-month SPEI covering the country's rainy agricultural season, which usually corresponds to the period of November to May for most of the country (Malawi National Statistical Office (MNSO), 2012). In this analysis, we specifically focus on SPEI values that correspond to the agricultural season during the year prior to each survey round in order to account for the longer-term consequences of a potential shock, and ensure that all households interviewed have endured the adverse event. In addition, the drought index values are joined to the household data and overlaid at the EA level. Several thresholds of the index are used to account for the impact of different levels of shock severity (either wet or dry) on diets⁶.

Moreover, it is important to underline both the temporal and spatial heterogeneity of weather shocks in our data. From Figure 1.2, we can notice that weather conditions were particularly dry in 2009, compared to Malawi's local historical average, as reflected by the 6-month SPEI values. On the other hand, conditions appeared more humid in 2012. Figure 1.3 further illustrates this by showing the average SPEI values per Traditional Authority (TA) over the agricultural season prior to each survey round, hence, for the years 2009, 2012 and 2015. Furthermore, these maps underline the asymmetrical distribution of dry and wet shocks across the territory and across time. In 2012, for instance, weather conditions were more humid in the Central region, and dryer in the Northern part of the country.

⁶In this analysis, a moderate shock is considered when SPEI \leq -1(dry shock) or SPEI \geq 1 (wet shock), while a severe shock takes place when SPEI \leq -1.5 (dry shock) or SPEI \geq 1.5 (wet shock). The cut-offs that define a weather shock as either moderate or severe are based on the classification of the SPEI values used in previous studies, including in Bo et al. (2015).

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Figure 1.2: Distribution of the SPEI

Notes: The panel represents the distribution of the 6-month SPEI values (for the period November - May) for the years preceding each household survey round. When the SPEI index is greater than or equal to 1 in absolute value, it is considered that a moderate weather shock has taken place. When the SPEI index is greater than or equal to 1.5 in absolute value, it is considered that a severe weather shock has taken place.



Figure 1.3: Average SPEI values per TA

Notes: Maps constructed by the author using the SPEI from the CEDA dataset (Peng et al., 2019). The three maps of Malawi represent the average values for the 6-month SPEI per TA, across the years 2009, 2012 and 2015 respectively (from left to right). The TAs in white represent missing values for the SPEI measure.

1.3.2.3 Forest cover

Lastly, regarding data on forest cover, it was obtained from the NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Vegetation Continuous Fields (VCF) data product, introduced by Hansen and Song (2018), which provides, at yearly intervals from 1982 to 2016, information on global fractional vegetation cover at a spatial resolution of 0.05 degrees (5,600 meters)⁷. Specifically, the VCF product represents the earth's surface as a gradation of three land cover types: percent tree cover, percent non-tree vegetation, and percent bare ground. We use the first layer, corresponding to percent tree cover, over the periods corresponding to the household survey rounds, which we also spa-

⁷The 5.6 km resolution of the forest data enhances the chances of accurately representing the percentage forest cover at the EA level, even after the offset of the GPS coordinate points (Johnson et al., 2013).

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tially join to the household data to extract the percentage of forest cover at the EA level. Figure 1.4 shows the variation in the percentage of forest cover per TA, as well as the location of the EAs from one survey round to another. We use the values of forest cover for the year prior to each survey round in order to account for the state of the forest during the same year as the potential weather shocks.

From the maps displayed below, we can first notice the variability of forest cover across the country. Higher percentages of forest cover are found in the North, which also corresponds to the least populated region in Malawi. Indeed, according to the country's latest Population and Housing Census (PHC), in 2018, the population in the Northern region was of 2,286,960 (corresponding to 13 percent of the total population), compared to 7,526,160 and 7,750,629 in the Central and Southern regions respectively (Malawi National Statistical Office (MNSO), 2019). On the other hand, forest cover appears to be the sparsest in the country's Central region, which is home to Malawi's capital city, Lilongwe. We can also observe variations in the percentage of forest cover across time, from one survey round to the next.



Figure 1.4: Average forest cover per TA and location of the EAs

Notes: Maps constructed by the author using VCF data and LSMS-ISA GPS coordinates for EAs in Malawi. The three maps represent the percentage of forest cover across Malawi for the years prior to each survey round, hence 2009, 2012 and 2015 (from left to right). The EAs expand from one year to the next due to the tracking of split-off households. For the EAs, the survey rounds correspond to the years 2010, 2013 and 2016.

1.3.2.4 Food security measure

To evaluate the impact of a weather shock on agricultural households' diets, and the role of forests as a safety net, we use a measure that aims at capturing, as much as possible, the diversity and energy sufficiency of diets at the household level. According to (Ruel and Cunningham, 2013), the intake of a variety of food items and food groups contributes to the provision of essential nutrients for human health and well-being. While attaining a diverse diet is a challenge in low-and-middle income economies, particularly amongst vulnerable communities whose diets are predominantly composed of starchy foods (Ruel and Cunningham, 2013), forests can play an important role in improving individual and household nutritional status as illustrated in Figure 1.1, and as highlighted in previous literature.

The measure of food security that is used in this paper is the Food Consumption Score (FCS), which was developed by the World Food Programme (WFP) in 1996 (World Food Programme, 2008). This index aims at capturing the diversity and the relative nutritional value of the food groups consumed by a household in the past 7 days, as well as the frequency at which they were consumed over this period (World Food Programme, 2008). More specifically, the score is calculated by aggregating the consumption frequencies of eight different food groups, and multiplying these frequencies by a standardized weight (see Appendix A.2 for details on the food groups and attributed weights) (World Food Programme, 2008). As described in the 2008 WFP guidelines for the FCS, higher weights are assigned to food items that are rich in protein and micronutrients, and which are high in energy. Staple foods will therefore be given a lower weight than animal-based products that are more nutrient dense (INDDEX Project, 2018). However, as underlined by (Wiesmann et al., 2009), one of the limitations of this index is that the WFP's standard nutritional value weights are not "based on a clearly defined nutritional metric" (INDDEX Project, 2018). For robustness, we therefore also conduct the estimations using the unweighted FCS, as well as the Food Variety Score (FVS), which represents the number of individual food items consumed at the household level over a 7-day reference period. The variety of food items consumed within certain food groups can, also, further result in better nutrient adequacy (Hodgson et al., 1994).

The weighted FCS has a possible range of 0 to 112⁸. Nonetheless, a score of 0 would signify that no food item from the eight food groups has been consumed by the household in the past week. In our data, the lowest value of the FCS is of 6.5. The distribution of the FCS per year is represented in Figure 1.5 below. It follows that, the higher the score, the more acceptable is considered the household's diet. According to the World Food Programme (2008)'s guidelines, a rise in the FCS corresponds to "an increase in the dietary diversity and/or frequency of consumption of one or more food groups - particularly those groups with larger weights".

 $^{^{8}}$ The unweighted FCS has a possible range of 0 to 56. In our data, the lowest value of the unweighted FCS is of 4.

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Low scores primarily reflect increases in the frequency of food consumption solely. A high FCS thus greatly depends on the introduction of new food groups in the household's diet (World Food Programme, 2008).

Although standard thresholds can be applied to the weighted index in order to dissociate households based on their food consumption levels, the continuous form of the FCS is preferred in this paper. Indeed, these cut-offs might not be universal and may thus not be appropriate for certain populations (World Food Programme, 2008). Nevertheless, the share of households with diets classified as either 'poor', 'borderline' and 'acceptable'⁹ according to these thresholds are represented in Appendix A.4. According to the data, the majority of households appear to have 'acceptable' diets, but this proportion has declined between 2010 and 2016. Additionally, the average frequency of consumption per food group, and per survey round, can be found in Appendix A.5.

Furthermore, there is a strong correlation between the Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS)¹⁰, as highlighted in Maxwell et al. (2013), and which is confirmed in our data. In the majority of contexts, both indicators can serve as measures of household dietary diversity, and valid proxies of households' access to 'energy sufficient' diets (Maxwell et al., 2013). However, by accounting for the frequency of consumption of different food groups over a week, the FCS provides a better understanding of households' usual dietary habits in comparison to the HDDS (INDDEX Project, 2018).

⁹Based on the WFP thresholds, households' food consumption status can be defined as 'poor' for scores ranging from 0-21; 'borderline' for scores ranging from 21.5 to 35; and 'acceptable' for scores above 35.

¹⁰As defined by the Food and Nutrition Technical Assistance Project (FANTA) (Swindale and Bilinsky, 2006), the HDDS is the count of unique food groups consumed within a household over a given reference period, and is usually computed using a total of 12 food groups. Unlike the FCS, it does not account for frequency of consumption, nor for food groups' different nutritional values.

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Figure 1.5: Distribution of the Food Consumption Score (FCS) *Notes*: The three panels represent the distribution of the Food Consumption Score (FCS) for the years 2010, 2013 and 2016, corresponding to each household survey wave.

The summary statistics for the rest of the variables mobilized in this analysis are in Appendix A.6.

1.3.3 Empirical strategy

The panel dataset described in Section 1.3.2 is used to assess the role of forests as a natural insurance for food security relative to potential alternatives accessible (or not) to households following a weather shock. By shedding light on the extent to which forests serve as an effective safety net for diets when other possible options are considered, we also aim to offer insights on some of the characteristics of communities that depend the most on forests for their food security and nutrition during challenging times.

1.3.3.1 Forests' role as a natural insurance relative to other options

To test the importance of forests as a natural insurance for food security relative to other safety nets, we estimate Equation 1.1 while differentiating the sample of households based on several potential risk-management options¹¹. These features, which may influence smallholders' level of vulnerability to an adverse event, include: livestock ownership (1= yes); the number of different durable assets owned (1= more than five durable assets owned); and participation in *ganyu* labor (1=

¹¹We chose to estimate separate regressions based on these three characteristics instead of adding triple interactions to facilitate interpretation of the results.

yes). The estimator is a linear model with high dimensional fixed effects (Correia, 2017), which is well suited for the continuous dimension of our main outcome of interest. The model specification can be written as the equation below:

$$Y_{i,v,t} = \beta_0 + \beta_1 Shock_{v,t-1} + \beta_2 Forest_{v,t-1} + \beta_3 Shock_{v,t-1} * Forest_{v,t-1} + \beta_4 X_{i,v,t} + \alpha_i + \gamma_t + \epsilon_{i,v,t}$$

$$(1.1)$$

where $Y_{i,v,t}$ represents the dietary diversity outcome for household $_i$ in village (EA) $_v$ at year $_t$, which specifically corresponds to the Food Consumption Score (FCS) at the household level, characterized as the frequency at which different food groups were consumed in the past week prior to the survey. Each food group is assigned a weight based on its nutrient density (World Food Programme, 2008). The higher the score, the more acceptable is considered the diet in terms of diversity and energy sufficiency.

Furthermore, $Shock_{v,t-1}$ represents the SPEI values at the EA level $_v$ at time $_{t-1}$, applied to Malawi's last agricultural season. The 6-month SPEI is derived by computing the average index values covering the period November to the end of April during the year prior to each survey round. As previously described, negative deviations from median conditions represent water deficits while positive deviations indicate a water surplus. Moreover, the SPEI variable is constructed as a binary variable that equals '1' if any dry or wet shock has occurred during the last agricultural season, and '0' otherwise. We estimate both the impact of a moderate weather shock, with SPEI values greater than or equal to 1 in absolute value, and of a more severe weather shock, with index values greater than or equal to 1.5 in absolute value. It is worth noting that there has been a greater number of moderate shocks compared to severe weather shocks over the period of study (see Appendix A.6). In addition, while the more severe shocks are primarily driven by positive SPEI values, moderate adverse weather events account for both the impact of a dry and wet shock on food security¹².

¹²Based on our data, overall, moderate dry shocks would account for 16.46 percent of total mod-

As mentioned previously, we regress the current food security outcome at the household level on lagged weather shocks in order to capture the lasting consequences of a weather anomaly on food security as well as the longer-term options households may have at hand to cope with past shocks. Moreover, several questions in the household questionnaire pertain to activities that have been undertaken by households in the 12 months prior to each survey round.

On the other hand, $Forest_{v,t-1}$ accounts for the percentage tree cover at the EA level $_v$ at time $_{t-1}$. The forest cover values are also lagged to consider the state of the forest during the same year as the shock. Forest cover at time $_t$ may have been altered by extraction of forest resources or expansion of agricultural land by communities impacted by the adverse weather event. Like the SPEI index, the forest data is overlaid at each household cluster via GIS. To correct for the fact that both the tree cover and weather data are aggregated at the EA level and that the estimations are conducted at the household level, resulting in several households having the same SPEI and tree cover values, the standard errors are clustered at the EA level. Moreover, clustering at this level permits to account for the risk sharing arrangements amongst households from the same community/EA.

Forests' ability to mitigate impacts of an adverse weather condition on our main variable of interest is then captured by the interaction $Shock_{v,t-1}*Forest_{v,t-1}$, where the weather variable is, as before, categorized such that '1' equals a weather shock (either wet or dry) and '0' reflects the absence of a weather shock, and where forest cover is kept as a continuous variable. We expect the sign to be positive to conclude that forests provide an effective safety net.

Finally, $X_{i,v,t}$ accounts for the different control variables that are included throughout this analysis due to their potential influence on food security and nutritional outcomes, as well as on households' general level of vulnerability. The explanatory variables included are the following: household size (count); livestock ownership (1= household has owned livestock in the past 12 months); real value of erate shocks and moderate wet shocks would represent 13.28 percent of total shocks. household durable assets (transformed in log and expressed in Malawian Kwacha (MWK)); real value of food expenditures in the past 7 days (also expressed in log and Malawian Kwacha (MWK)); distance to the nearest population center (in km); and distance to the nearest lake (in km). In addition, both household and year fixed effects are included, respectively expressed by α_i and γ_t . Household fixed effects control for unobserved heterogeneity at the household level, hence limiting omitted variable biases. Year fixed effects account for external shocks all households may encounter, such as price shocks, and $\epsilon_{i,v,t}$ is the random error term.

Time-varying household attributes such as the size of the household are controlled for as they can influence the quality of households' diets. Indeed, an increase in the number of members within a household is often associated with lower dietary diversity. Vis et al. (1975) find a link between the decline in food intake per capita and an increase in family size, reflecting lower availability of food within larger families. More recently, Huluka and Wondimagegnhu (2019) show that a rise in household size increases the likelihood of having a lower dietary diversity at the household level. Indeed, as family size expands, the allocation of household resources is likely to be subject to greater competing needs, especially if the family's income sources are limited (Huluka and Wondimagegnhu, 2019). Nevertheless, in some instances, household dietary diversity may increase as the demand for food amongst adults in the family rises (Christian et al., 2019).

Moreover, livestock possession can also influence food security and nutrition at the household level. First, they comprise a source of wealth and can play an important role in agricultural households' adaptive capacity (Cooper and Wheeler, 2016). Indeed, livestock can be acquired for saving purposes¹³ during favorable times, and then be sold in the event of a crisis to cope with the adverse event (Jodha, 1978, Corbett, 1988, Smucker and Wisner, 2008, Silvestri et al., 2012,

¹³As described in Girard et al. (2021), small stock, such as poultry, will often be used for saving purposes, as it is less costly and easier to liquidate. As for productive assets such as cattle, they will generally be sold in a second phase depending on how severe the shock is. As highlighted in Corbett (1988) and Smucker and Wisner (2008), shock-stricken households will first attempt to cope with the adverse event while not depleting their productive assets.

Wunder et al., 2014b). Moreover, Acosta et al. (2021) specifically find that livestock can serve as a buffering mechanism following droughts. Livestock can also directly affect food security by increasing the availability and consumption of animal-based products, including meat, dairy products and eggs, and hence improve household nutritional well-being (Randolph et al., 2007).

Similarly, the value of durable assets possessed can be an indicator of household wealth, and represent a crucial coping mechanism when they are sold by farmers to smooth consumption following a shock, and subsequently prevent food shortages (Lutomia et al., 2019, Girard et al., 2021). The positive correlation between asset ownership and nutrition is also highlighted in Guo (2011) and in Reincke et al. (2018). We also include the value of household food expenditures in the past 7 days as it can capture a revenue effect, and thus reflect an increase in household income, with a direct influence on households' food consumption. The positive association between food expenditures and the diversity of households' diets is for instance demonstrated by Thorne-Lyman et al. (2010) in a study on Bangladesh.

Lastly, we account for households' distance (in km) to the nearest population center of more than 20,000 residents¹⁴, as well as their distance (in km) to the nearest lake, amongst three of the country's largest lakes, namely Lake Malawi (also known as Lake Nyasa), Lake Chilwa, and Lake Malombe¹⁵. Distance to the nearest large town allows to capture households' access to an economic center, which can be crucial to obtain access to critical resources, including a variety of nutritious foods, and hence maintain food security levels. Households that reside in the vicinity of lakes, on the other hand, could potentially have access to an important source of fish for own consumption and/or for sale, as well as to other economic activities that can benefit their well-being and overall livelihoods.

¹⁴This information is derived from the World Gazeteer Towns data, rendered available within the framework of the LSMS-ISA geospatial data. The distances are calculated using the unmodified GPS coordinates (i.e., those that have not been offset by the LSMS-ISA team for confidentiality purposes).

¹⁵Distances to the nearest lake have been produced by the authors using the GPS coordinates available in the household data (and available at the level of the EA), and shapefiles of Malawi's major water bodies.

1.4 Results

This section presents the results derived from the econometric analyses conducted. As described, they aim at shedding light on the role of forests as a safety net relative to a few, possible, alternative risk-management options that could be adopted by agricultural households in the aftermath of a weather shock.

1.4.1 Forests' role as a natural insurance relative to other coping mechanisms

We first run the estimates for all households while considering forests as a buffer against any type of shock (either wet or dry) Table 1.1. We then distinguish between both types of shocks in Table 1.2. Subsequently, with the objective of determining to what extent does the effectiveness of forests' safety net use depends on other potential insurance options, we segment the sample based on other possible alternatives including livestock ownership Table 1.3; durable asset possession Table 1.4; and participation in a form of informal off-farm labor known as *ganyu* Table 1.5.

1.4.1.1 Whole sample

Table 1.1 displays the results from the estimations pertaining to forests' role as a safety net for food security following a weather shock for all households, while accounting for the impact of both a moderate and a severe weather shock. Table 1.2 shows how the influence of forests may vary depending on whether the shock is characterized as wet or dry.

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	Moderate		Severe			
Dependent variable: Food Consumption Score (FCS $_{i,v,t}$)						
Variables	(1)	(2)	(3)	(4)		
Shock _{$v,t-1$} (ref: no shock)	-3.880**	-4.287***	-3.486**	-3.199**		
	(1.603)	(1.353)	(1.707)	(1.473)		
Forest $_{v,t-1}$ (%)	-0.213***	-0.147***	-0.191***	-0.116**		
,	(0.058)	(0.049)	(0.059)	(0.051)		
$\mathbf{Shock}_{v,t-1} \ \mathbf{X} \ \mathbf{Forest}_{v,t-1}$	0.279***	0.347***	0.315**	0.317***		
	(0.104)	(0.093)	(0.122)	(0.102)		
HH size $_{i,v,t}$		-0.754***		-0.757***		
		(0.165)		(0.165)		
$\text{Liv}_{i,v,t}$ (ref: no livestock)		1.840***		1.849***		
		(0.664)		(0.661)		
Assets $_{i,v,t}$ (log, real value MWK)		1.580***		1.573***		
		(0.179)		(0.180)		
Food $\text{Exp}_{i,v,t}$ (log, real value, MWK)		8.696***		8.676***		
		(0.423)		(0.426)		
Dist Center $_{i,v,t}$ (km)		-0.002		-0.001		
		(0.037)		(0.037)		
Dist Lakes $_{v,t}$ (km)		-0.025		-0.029		
		(0.025)		(0.026)		
			,			
Household Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark		
Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark		
Nb. of households	2,424	2,283	2,424	2,283		
Observations	7,243	6,432	7,243	6,432		
R-squared	0.613	0.702	0.613	0.701		

Table 1.1: Forests' role as a	safety net for food	security
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Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). In columns 1 & 2 the weather shock variable (Shock_{v,t-1}) corresponds to a moderate weather shock (SPEI index greater than or equal to 1 in absolute value). In columns 3 & 4, the weather shock variable corresponds to a more severe weather shock (SPEI index greater than or equal to 1.5 in absolute value).

The results first highlight that a weather shock, whether it is characterized as moderate or severe, has a negative and statistically significant impact on the main outcome of interest, which aims to capture the diversity and energy sufficiency of households' diets. When no explanatory variables are accounted for (columns 1 & 3), the occurrence of a moderate weather shock during the past agricultural season decreases the FCS by 3.88 units, while a severe weather shock leads to a 3.486-unit decrease in the food security indicator. As a broad example, a loss of about 4 units in the FCS could signify that households have not consumed main staples for two days in the past week, or that they have not consumed fruits for four days over the last 7 days¹⁶. In reality, however, the fall in the FCS is likely to be associated with a decrease in the consumption of various food groups of different nutritional densities, which we cannot precisely identify by considering the FCS alone. Nonetheless, when running the estimates for each of the eight food group scores that constitute the FCS¹⁷, we observe that a shock, whether moderate or severe, leads to a fall in the individual score¹⁸ for fruits, vegetables and milk/milk products. A decrease in the consumption of fruits and vegetables one year after a shock is in line with Salazar-Espinoza et al. (2015), who find, in the context of Mozambique, that agricultural households move out of non-staple crops one year after a weather-related shock in order to limit high-risk cropping activities. Specifically, the authors show that, following a flood, farmers shift away from horticulture and permanent crops, while, in the aftermath of a drought, they tend to "reallocate resources away from cash and permanent crops". As for milk and other dairy products, a fall in their intake could reflect a change in the livestock portfolio of households in response to an adverse event. Indeed, following the weather shock, households may have

¹⁶Main staples having a weight of 2, if households were not to consumed main staples for two days over a week, their FCS would decrease by 4 units (at the maximum, main staples can contribute to the FCS by 14 units if they are consumed every day of the week prior to the survey). Similarly, fruits being attributed a weight of 1 (as well as vegetables), if households were not to consume any type of fruit during two days, their FCS would decrease by 2 units (at the maximum, fruits can contribute to the FCS by 7 units if they are consumed every day of the week prior to the survey) (see Appendix A.2).

¹⁷Detailed results upon request.

¹⁸The score associated with each food group refers to its weight multiplied by the number of days over a week it was consumed by a household.
invested more into livestock types that are both more resilient to shocks and easier to liquidate (Abay and Jensen, 2020). In contrast to cattle for instance, poultry and other small stock can easily be exchanged for cash (Ngigi et al., 2015). Similarly, small ruminants, including goats and sheep, are more resilient to water and feed scarcity resulting from rainfall anomalies than larger ruminants such as cattle (Bati, 2014). As such, one year after the occurrence of a weather shock, households in our sample may have reduced their investment in livestock that can produce large quantities of milk such as dairy cattle, which could explain the fall in the dairy products score¹⁹.

Coming back to the main results, we can note that the negative effect of a shock, whether moderate or severe, slightly increases when including the complete set of covariates (columns 2 & 4). Nonetheless, we can observe that the interaction between $Shock_{v,t-1} * Forest_{v,t-1}$ positively influences the food security indicator for all estimations. More precisely, for the full model (columns 2 & 4), when forest cover is equal to one standard deviation above its mean (i.e., a forest cover of 20.9 percent) at the time of a moderate shock, it contributes to an increase in the FCS by 2.975 units at a one percent level of significance²⁰. When a severe weather shock has occurred during the last agricultural season, a forest cover of close to 21 percent in t_{t-1} contributes to a 3.434-unit rise in the FCS. It is worth noting that when forest cover is equal to its average value (i.e., 13.2 percent for the full sample), it appears to provide no buffer against shocks. The influence of a weather shock on the FCS for different forest cover values are displayed in Appendix A.7. The rise in FCS that results from forests may be linked to a greater consumption or sale of wild foods, or other forest products. From our data, 26.42 percent of households impacted by a moderate shock consumed wild foods in the last 7 days (compared to 24.99 percent for those not impacted). This share rises to 27.49 percent in the aftermath

¹⁹While we observe a fall in the consumption of dairy products, we do not observe a fall in the consumption of meat, which remains consistent with our hypothesis.

²⁰In our full sample, the average tree cover is of 13.2 percent with a standard deviation of 7.7. A tree cover of 20.9 percent at the time of a moderate shock therefore contributes to a 3-unit increase in the FCS (while the occurrence of a moderate shock alone leads to a fall in the FCS of about 4 units).

of a severe shock (compared to 25.11 percent for those not impacted).

These findings suggest that greater percentages of forest cover can play an important role in mitigating the negative impacts of a weather anomaly on diets. As described previously, during food shortages, forests can render adequate food available for direct consumption (Johns et al., 2006), and can provide a source of complementary income through the sale of NTFPs (Angelsen and Wunder, 2003, Paumgarten, 2005). Additionally, forest environments can help mitigate the impacts of droughts through the provision of clean water, and can absorb rainwater surplus, helping to prevent floods (European Environment Agency, 2015). These findings are consistent with the analysis of Mulungu and Manning (2023) that also shows that forests can serve as a safety net for agricultural households' food security following a weather shock.

As for the negative sign of the individual forest cover variable, it could be explained by the positive association that can exist between forests and poverty, as highlighted in Neumann and Hirsch (2000). While forests can represent a valuable safety net, and hence make a difference between bad and good nutrition (Angelsen and Wunder, 2003), their presence can also translate remoteness to markets and limited access to more remunerative activities (Angelsen and Wunder, 2003), and, hence, result in a lower consumption of diverse and nutritious foods. However, it should be noted that, with the inclusion of household fixed effects, the coefficient on the percentage forest cover, in the absence of a weather shock, is estimated on variations in tree cover over the past. These forest cover changes may have been impacted by past weather-related shocks, as well as by the strategies households may have adopted to face these adverse events. Indeed, although trees, including *miombo* trees, have the ability to withstand extreme weather events such as droughts through carbohydrate storage and the internal recycling of nutrients, their stores may be undermined by successive droughts or indirectly through fires (Campbell, 1996). Additionally, in response to past shocks, communities may have increased their collection of forest products, potentially depleting resources, or ex-

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panded cropland to the detriment of forests (Desbureaux and Damania, 2018). As a result, the change in tree cover, which is of importance for the estimation of the coefficient associated with the forest cover measure (when a weather shock is set to 0), is endogenous.

Regarding the rest of the variables, they have their expected sign, notably those that may reflect household wealth. Indeed, when weekly food expenditures and the reported value of durable assets rise, households' consumption of a variety of food groups, and the frequency at which they are consumed, consistently expands as well. The same is observed for livestock possession. As for households' distance to a population center, and their distance to one of Malawi's three major lakes, these variables have no significant impact on the outcome. Nonetheless, with the inclusion of household fixed effects in our models, the coefficients associated with our independent variables are estimated only for those households for which these measures have changed across time. In the case of the last two variables mentioned, their respective coefficients are only estimated for those households that have moved in 2013 or 2016 with respect to their location of 2010²¹. Indeed, households that have not moved remained at the same distance of a population center or a major lake from 2010 to 2016, which is accounted for by the household fixed effects.

Additionally, in Table 1.1, we run the same estimates as in Table 1.2 while making a dissociation between a dry shock and a wet shock. The occurrence of a dry weather shock negatively impacts the FCS whether we account for explanatory variables or not. Indeed, in column 1, which includes the results in the absence of control variables, we can observe that the occurrence of a dry weather shock during the last growing season prior to the survey leads to a decrease in the FCS by 4.396 units. When the covariates are accounted for (column 2), the dry shock leads to a

²¹According to our data, about 54 percent of households have moved in 2013 or 2016 with respect to their baseline location. However, amongst these movers, some may have remained in the same village. For these households, measures related to distance may also be accounted for by the household fixed effects as they should still reside in the same EA.

fall in the FCS by 4.807 units. On the other hand, a wet shock has a negative effect on food security (though at a 10 percent significance level) only when including the full set of covariates. Additionally, solely the interaction between a dry shock and percentage forest cover is statistically significant and positive in both columns. These results suggest that forests serve as an effective safety net for the FCS especially in the aftermath of a drought. Forests may not play a role in mitigating effects to a wet shock in this context, as, based on the maps in Figure 1.3, SPEI values in 2012 were especially positive in Malawi's Central region, where forest cover is sparser (compared to the North for instance).

For robustness, we run the series estimations in Table 1.1 and Table 1.2 while using the unweighted FCS and the Food Variety Score (FVS) as the main outcomes of interest (see Appendix A.8). The results remain consistent. It is worth noting, nonetheless, that a wet weather shock appears to have a negative impact on the unweighted FCS. Additionally, forests seem to offset its effects (Appendix A.9). Main staples, whose high frequency of consumption is particularly captured to by the unweighted FCS, may be sensitive to rainwater excess. Access to forest products may allow to compensate for the potential crop damage from excessive rain.

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<i>Dependent variable</i> : Food Consumption Score (FCS _{i,v,t})							
Variables	(1)	(2)					
Dry Shock $_{v,t-1}$ (ref: no dry shock)	-4.396**	-4.807***					
	(2.054)	(1.680)					
$\operatorname{Forest}_{v,t-1}$	-0.183***	-0.116**					
	(0.060)	(0.051)					
Dry Shock _{$v,t-1$} X Forest _{$v,t-1$}	0.373***	0.437***					
	(0.122)	(0.104)					
Wet $\text{Shock}_{v,t-1}$ (ref: no wet shock)	-2.520	-2.739*					
	(1.757)	(1.538)					
Wet $Shock_{v,t-1}$ X $Forest_{v,t-1}$	0.006	0.060					
	(0.120)	(0.115)					
Control variables		\checkmark					
Household Fixed Effects	\checkmark	\checkmark					
Year Fixed Effects	\checkmark	\checkmark					
Nb. of households	2,424	2,283					
Observations	7,243	6,432					
R-squared	0.615	0.703					

Table 1.2: Difference between dry and wet shocks

Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). A dry shock corresponds to SPEI values less than or equal to -1. A wet shock corresponds to SPEI values greater than or equal to 1.

1.4.1.2 Livestock

To test the role of forests relative to other potential buffers against shocks, we first estimate Equation 1.1 while making a distinction between households that have owned livestock in the past 12 months and those that have not Table 1.3. Livestock can include cattle, as well as small stock such as poultry, and, as described, is widely used in Sub-Saharan Africa as a coping strategy (Girard et al., 2021).

	Mode	rate	Severe					
Dependent variable: Food Consumption Score (FCS $_{i,v,t}$)								
	No livestock	Livestock	No livestock	Livestock				
Variables	(1)	(2)	(3)	(4)				
$Shock_{v,t-1}$ (ref: no shock)	-4.897***	-3.045	-3.645*	-4.681**				
	(1.574)	(1.898)	(1.951)	(2.008)				
$\operatorname{Forest}_{v,t-1}$ (%)	0.005	-0.264***	0.031	-0.231**				
	(0.065)	(0.096)	(0.064)	(0.093)				
$\mathbf{Shock}_{v,t-1} \ \mathbf{X} \ \mathbf{Forest}_{v,t-1}$	0.375***	0.219	0.371***	0.265*				
	(0.084)	(0.138)	(0.089)	(0.141)				
Control variables	\checkmark	\checkmark	\checkmark	\checkmark				
Household Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark				
Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark				
Nb. of households	1,103	1,019	1,103	1,019				
Observations	2,691	2,497	2,691	2,497				
R-squared	0.760	0.678	0.760	0.678				

Table 1.3: Forests' role as a safety net relative to livestock

Standard errors in parentheses clustered at the EA level.

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

From the results displayed in Table 1.3, we can observe that a weather shock, whether it is moderate or severe, negatively affects the FCS of households that have not owned livestock in the past 12 months (columns 1 & 3). Indeed, the occurrence of a moderate adverse event reduces these households' FCS by 4.897 units (column 1), while a more severe shock decreases their dietary outcome by 3.645 units (column 3). Again, the smaller effect size associated with a more severe shock could be explained by the fact that, in the aftermath of a severe weather event, households may mobilize a greater number of insurance options to cope with its effects, as compared to with a moderate shock. As for households that

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). In columns 1 & 2 the weather shock variable (Shock_{v,t-1}) corresponds to a moderate weather shock (SPEI index greater than or equal to 1 in absolute value). In columns 3 & 4, the weather shock variable corresponds to a more severe weather shock (SPEI index greater than or equal to 1.5 in absolute value). Furthermore, columns 1 & 3 correspond to the household sample that has not owned livestock in the past 12 months prior to the survey. On the other hand, in columns 2 & 4 households have owned livestock in the past year. The measure of livestock ownership is not included as a control variable.

have possessed livestock in the past year, their FCS is only negatively impacted by a severe weather shock (column 4).

When it comes to forests' natural insurance role captured by the interaction between Shock_{v,t-1} X Forest_{v,t-1}, we can notice that, for households that have not owned livestock in the past year, the interaction term always has a positive and significant impact on the outcome of interest whether the shock is characterized as moderate or severe. In contrast, the interaction term only has a positive and significant effect in the context of a severe shock for the other sample (though at a low level of significance). These results first suggest that forests provide an effective safety net for food security when households do not have livestock as a potential insurance mechanism. Additionally, they imply that forest resources may potentially also serve as a buffer against shocks when other options may be available (although, at this stage, evidence is weak). In this case, in the aftermath of a severe shock, livestock, which can also be vulnerable to adverse weather conditions, might not be sufficient to maintain food security levels. Products and services from forest environments may, potentially, therefore represent a complementary insurance option.

Furthermore, it is worth noting that, given the inclusion of household fixed effects in our models, the regressions are solely estimated for those households that appear several times in the same category (i.e., either in the "no livestock" category or in the "livestock" category). Indeed, a same household may have reported to have owned livestock in the past 12 months in 2010, but not in 2016. This consideration also holds when separating the sample based on the number of durable goods owned Table 1.4 and according to households' participation in *ganyu* labor in the past year Table 1.5.

1.4.1.3 Durable goods

Secondly, we differentiate the sample between households that own five different durable goods or less (which approximately corresponds to the sample mean) and households that own more than five durable goods Table 1.4.

	Mod	erate	Severe					
Dependent variable: Food Consumption Score (FCS _{i,v,t})								
	Assets≤5	Assets>5	Assets≤5	Assets>5				
Variables	(1)	(2)	(3)	(4)				
Shock _{$v,t-1$} (ref: no shock)	-2.747*	-6.081**	-4.364**	-4.050				
	(1.568)	(2.747)	(1.922)	(2.915)				
$\operatorname{Forest}_{v,t-1}$ (%)	-0.098	-0.165*	-0.080	-0.106				
	(0.064)	(0.092)	(0.059)	(0.099)				
$\mathbf{Shock}_{v,t-1} \ \mathbf{X} \ \mathbf{Forest}_{v,t-1}$	0.216**	0.468***	0.317**	0.352**				
	(0.105)	(0.132)	(0.124)	(0.153)				
o 1 1 1	,	,	,	,				
Control variables	\checkmark	\checkmark	\checkmark	\checkmark				
Household Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark				
Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark				
Nb. of households	1,609	802	1,609	802				
Observations	4,092	1,968	4,092	1,968				
R-squared	0.640	0.734	0.640	0.733				

Table 1.4: Forests' role as a safety net relative durable goods

Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). In columns 1 & 2 the weather shock variable (Shock_{v,t-1}) corresponds to a moderate weather shock (SPEI index greater than or equal to 1 in absolute value). In columns 3 & 4, the weather shock variable corresponds to a more severe weather shock (SPEI index greater than or equal to 1.5 in absolute value). In columns 1 & 3, the sample corresponds to households that own five durable goods or less at the time of the survey (which pertains approximately to the mean of the full sample). In columns 2 & 4, the sample corresponds to households that own more than five different durable goods. The value of assets is not included as a control variable.

Overall, there are little disparities between both samples. One of the main dif-

ferences includes the absence of effect of a severe shock on the FCS of households that own more than five durable goods. Otherwise, the interaction term between forests and a weather shock remains positive and significant both for households that are poorer in terms of durable goods and for those that own a greater number of assets. Nonetheless, as opposed to the other alternatives to forests we investigate in this work (i.e., livestock and ganyu labor), the number of durable goods possessed by households is not necessarily measured in t_{t-1} , which corresponds to the period during which the shock has taken place²². It is therefore possible that households have sold assets right after the occurrence of the adverse weather event. Consequently, as a robustness check, we divide the sample into quartiles based on the value of durable goods households have reported to own²³. It appears reasonable to believe that households that fell under the 1st quartile at the time of the survey did not belong to the 3rd or 4th quartile one year prior to the latter. Doing so therefore permits to consider the role of forests as a buffer against shocks depending on where households stand in terms of asset wealth, which was likely to be similar at the time of the shock 24 .

When considering the descriptive statistics for livestock ownership and participation in *ganyu* labor according to these different quartiles (see Appendix A.10), the argument according to which most households did not switch categories over a year seems likely. Indeed, on average, 60 percent of households in quartile 1 reported to have participated in *ganyu* labor over the past 12 months, compared to 20 percent of households in the 4th quartile. In fact, the share of households that participate in *ganyu* labor decreases as the quartile level rises. *Ganyu* labor being a low-return and informal off-farm labor activity, as described, the most asset-poor may allocate labor to this market in the absence of more remunerative activities. As for livestock ownership, the illustration provided by the descriptive statistics is

²²Forest cover is also measured in t-1.

²³The value of assets measure represents the sum of the value associated with each durable good owned by a household (expressed in log, real terms, and in MWK).

²⁴Although a move from the 3^{rd} to 2^{nd} quartile could be possible if households sold assets right after the shock, it seems unlikely that households could shift from being in the 1st to being in 4^{th} quartile over one year.

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also coherent with our argument. The highest share of livestock owners are concentrated in the 2nd and 3rd quartiles - quartile 1 may be comprised of households that do not have enough means to own livestock (their maintenance requires a certain amount of expenditures (Ssewamala, 2004); as for quartile 4, it may include households with access to more off-farm activities for instance.

Furthermore, the results pertaining to the division of the sample by asset quartile (see Appendix A.11, show that, in the aftermath of a moderate shock, only households pertaining to the 4th quartile potentially turn to forests following a shock (though, the weather shock variable in itself has no effect on their food security). Compared to the other quartiles, quartile 4 comprises the lowest share of households that own livestock and participate in *ganyu* labor, which could explain why these households may use forest resources as a buffer in addition to or as a substitute to assets. In fact, this result could be in line with Mulungu and Kilimani (2023), which find that access to forest resources can limit households' dependence on costly insurance mechanisms such as liquidating private assets. Selling off assets can be characterized as a costly insurance option, in contrast to extracting common pool resources, as it can lead to a reduction in households' future productive capacity and overall consumption, with the ultimate risk of trapping individuals into poverty (Carter and Lybbert, 2012).

On the other hand, in the aftermath of a moderate weather shock, households in the lowest quartiles may turn to *ganyu* and/or livestock first. Yet, when a more severe shock hits, there is evidence that households in the lowest asset quartiles (in this case, the 2^{nd} quartile) turn to forests as well, potentially as a complement to other alternatives such as livestock and *ganyu*. Based on these results, forests appear to play a role in moderating the impacts of a shock on food security even when alternatives such as assets are potentially available to households. However, the estimations derived from the sub-samples categorized into quartiles should be interpreted in light of significantly reduced sample sizes.

1.4.1.4 Ganyu

Finally, we investigate forests' insurance properties based on whether households have participated in *ganyu* labor over the past 12 months or not Table 1.5. *Ganyu* labor can be defined as a form of informal off-farm labor often practiced on another household's farm and is widely used in Malawi as a risk-management strategy (Michaelowa et al., 2010). As underlined in Girard et al. (2021), along with the sale of assets and the collection of forest products, engaging in off-farm work is commonly used as a coping strategy in agricultural settings.

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	Mode	rate	Severe					
Dependent variable: Food Consumption Score (FCS _{i,v,t})								
	No Ganyu	Ganyu	No Ganyu	Ganyu				
Variables	(1)	(2)	(3)	(4)				
Shock _{$v,t-1$} (ref: no shock)	-5.723***	-4.021*	-4.068*	-2.377				
	(2.117)	(2.153)	(2.243)	(2.166)				
$\operatorname{Forest}_{v,t-1}$ (%)	-0.175**	-0.091	-0.142	-0.079				
	(0.085)	(0.082)	(0.089)	(0.079)				
$\mathbf{Shock}_{v,t-1} \ \mathbf{X} \ \mathbf{Forest}_{v,t-1}$	0.506***	0.270**	0.423***	0.349**				
	(0.142)	(0.128)	(0.149)	(0.137)				
Control variables	\checkmark	\checkmark	\checkmark	\checkmark				
Household Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark				
Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark				
Nb. of households	1 210	883	1 210	883				
Observations	2 055	2 024	2 055	2 024				
Descuered	2,933 0 716	2,024 0.600	2,933 0 714	2,024				
K-squareu	0./10	0.090	0./14	0.090				

Table 1.5: Forests' role as a safety net relative to ganyu

Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). In columns 1 & 2 the weather shock variable (Shock_{v,t-1}) corresponds to a moderate weather shock (SPEI index greater than or equal to 1 in absolute value). In columns 3 & 4, the weather shock variable corresponds to a more severe weather shock (SPEI index greater than or equal to 1.5 in absolute value). In columns 1 & 3, the sample corresponds to households that have not participated in the *ganyu* labor market over the past 12 months. In columns 2 & 4, the sample corresponds to households that have participated in the *ganyu* labor market over the past 12 months.

The occurrence of a moderate weather shock negatively and significantly impacts households' food security within both samples (columns 1 & 2). Yet, when looking at columns 3 & 4, for which $\text{Shock}_{v,t-1}$ corresponds to a more severe weather anomaly, we can observe that only households that have supplied labor to the *ganyu* market do not experience any decrease in their FCS following a weather shock (column 4). On the other hand, for households that have not engaged in *ganyu* labor, a severe shock decreases their FCS by 4.068 units (column 3) (though at a low level of significance).

As for the role of forests as a safety net, which is captured by the interaction term expressed as $\text{Shock}_{v,t-1}$ X Forest_{v,t-1}, it appears to be effective both for households that have not participated in *ganyu* labor in the past year, and for those that have. Although both samples cannot be compared, these results suggest that forests play a role in mitigating negative impacts to food security following a shock even for households that potentially have *ganyu* labor as a risk-management option.

In line with the previous results, forests appear to provide a buffer against shocks even when other alternatives are possibly available to households. As such, agricultural communities may turn to forests both when they do not have any other options (which could be translated by the results in columns 1 & 3 of Table 1.3, Table 1.4, and Table 1.5) and when they need to complement other insurance alternatives. Households that supply labor to the *ganyu* market may therefore also engage in the collection of forest resources during difficult times or as part of their overall livelihood strategy. These activities, in fact, share similar characteristics: both are low-return activities that are often associated with poverty traps in the literature (Angelsen and Wunder, 2003, Michaelowa et al., 2010). Nonetheless, as seen in Table 1.4 and in Appendix A.11, even the wealthier households in term of assets seem to rely on forests to cope with a shock. Although forest-related activities offer small returns, collecting forest products during difficult times may prevent the reliance on costly coping mechanisms, which can, ultimately, enhance poverty as described.

1.5 Discussion and conclusion

The aim of this research is to investigate the role of forests as an insurance mechanism for primarily agricultural households in the aftermath of a weather shock in a developing country context. Our contribution is two-fold. First, while the literature on forests' insurance properties has rather focused on indicators pertaining to the allocation of labor, such as in Pattanayak and Sills (2001) or income, such as in Noack et al. (2019), this paper looks at food security to capture the overall well-being of communities that have limited access to markets and that rely heavily on low-input subsistence agriculture. Additionally, looking at agricultural households' diets allows to account for forests' market and non-market benefits. To our knowledge, only the work by Mulungu and Manning (2023) provides evidence on forests' ability to protect household dietary diversity following a weather shock. With respect to this work, our main contribution includes demonstrating to what extent do forests represent an effective safety net for food security following a weather shock when other alternatives may be available. We do so while dissociating shocks according to varying severity levels, and providing some answers on potential heterogeneous impacts between dry and wet shocks.

We find that, overall, forests play an important role in protecting households' food security following a weather shock, in line with (Mulungu and Manning, 2023). According to our results, the buffer offered by forests seems particularly effective against droughts, although some evidence for one particular indicator suggest that they may also protect food security following a wet shock. Moreover, looking more deeply into sources of heterogeneity, we show that forests generally represent an effective safety net for food security in the aftermath of a shock whether potential risk-management options are available or not. Precisely, house-holds that do not own livestock, that are at the mean or below in terms of the number of durable goods owned, or that do not supply labor to the *ganyu* market, appear to benefit from forests' natural insurance. These households may rely on forests in the absence of other alternatives, which would be in line with previous studies, including Wunder (2001), Pattanayak and Sills (2001) and Baland and Francois (2005), that showed that forests are used as a safety net by agricultural households that have limited options to smooth consumption.

Nonetheless, when segmenting the sample into asset quartiles, forests do not

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seem to play any role for households in the lowest quartiles in the aftermath of a moderate weather shock. The lowest quartiles being comprised of the largest share of livestock owners and *ganyu* laborers, these households may not necessarily need to turn to forests when a moderate weather shock hits as livestock and *ganyu* may already provide effective buffers (these households may benefit from both of these potential risk-management options at the same time). Furthermore, as highlighted in Andrews and Mulder (2022), because households with limited resources may potentially already exhibit a high dependency on forests, their reliance may not increase further, even after shock. Nevertheless, our findings suggest that they may rely on forest resources when a severe shock occurs.

Additionally, we show that households for which one of these alternatives may be available (i.e., livestock, assets, and ganyu labor) also benefit from forests' insurance properties. While livestock owners may not turn to forests in the aftermath of a moderate shock, we observe weak evidence that they may do so following a severe weather shock. Although livestock can represent an effective safety net, they are also vulnerable to adverse weather conditions, and hence, may not represent a sufficient buffer against a severe shock. Forest resources may therefore offer an additional risk-management option. As for assets, our results suggest that the wealthier households in terms of durable goods may also turn to forests in the aftermath of a shock. Based on descriptive statistics for livestock ownership and ganyu labor according to asset quartile, we can see that the largest quartiles, namely the 3nd and 4th quartiles, are comprised of the lowest shares of livestock owners and ganyu laborers, as opposed to the two lowest quartiles. Households that are richer in terms of assets may therefore not have livestock or off-farm labor as potential buffers against shocks. As such, turning to forests when an adverse weather event hits may prevent them from liquidating their private assets, which could, ultimately, trap them into poverty by reducing their consumption and future productive capacity (Carter and Lybbert, 2012). This line of reasoning is in accordance with Mulungu and Kilimani (2023), which find that access to common property forests reduces households' reliance on costly coping mechanisms.

Finally, when it comes to *ganyu* labor, we also find that forests' insurance properties remain effective even for households that have engaged in this off-farm activity over the past year. Like forests, *ganyu* labor is a low-return activity that can be associated with a poverty trap (Angelsen and Wunder, 2003, Michaelowa et al., 2010). Individuals who take part in this type of labor may therefore also rely on forests during difficult times.

The results of this empirical work therefore suggest that forests can be fundamental in protecting food security following a weather shock both amongst households that have limited insurance options and/or that may need a complementary insurance option to cope with a weather shock. In our context, agricultural households' may add forest resources to their portfolio of potential risk-management options either because the alternatives available are not sufficient to deal with the shock (e.g., livestock may also suffer from a drought or flood) or to avoid relying on costly coping mechanisms, which could affect their livelihoods in the future.

Nonetheless, there are several caveats with respect to the analysis that should be underlined. Firstly, in contrast to livestock ownership and participation in *ganyu* labor, the durable assets owned by households do not necessarily refer to assets possessed over the last 12 months prior to the survey. As a result, the durable assets variable used to differentiate the household sample may have been impacted by the weather shock in period t-1. Indeed, households may have sold assets as soon as the weather shock hit, leading them to own a smaller number of durable goods at the time of the interview, with potential impacts on food security. To remedy this issue, as a robustness check, we divide the household sample by quartile based on the value of durable assets that households possess. We do so to test the role of forests as a safety net depending on where households stand in terms of wealth. Indeed, we anticipate that households are unlikely to move from being in the 4th quartile to the 1st quartile, for instance, even if they sold assets following a weather shock. This assumption seems to hold when looking at descriptive statistics for livestock ownership and ganyulabor based on quartiles.

Secondly, our analysis may be subject to possible selection issues whereby individuals may partially select into living in proximity to forests giving their insurance properties for instance, or conversely, far from forests to have an increased access to markets. Conducting the analysis in another context may therefore be useful to ensure external validity.

With these considerations in mind, our findings call for the need to implement interventions that aim at expanding the variety of strategies agricultural communities can rely on to adapt and cope with adverse events. For communities with limited risk-management options, improving asset accumulation, including livestock and durable goods, can play an important role in increasing their adaptive capacities while alleviating their reliance on forest resources, and on other activities that could, potentially, constitute a poverty trap. Enhancing the development of road and telecommunication infrastructure is also crucial to foster rural residents' access to markets (Murendo et al., 2020), and, thus, their ability to depend on formal insurance mechanisms such as credit or insurance, in addition to informal risk-management options.

Moreover, considering the alarming deforestation rates across the world and the increase in the frequency and intensity of extreme weather events, these findings place an emphasis on the urgent need to preserve and sustainably manage forests for improved human and planetary health. Additionally, because forests' natural insurance role is likely to be linked to the collection of forest resources by rural communities, which can lead to the overexploitation and degradation of forest environments (Delacote, 2007, 2009), policy makers face a dual challenge. The first is to preserve access to forests for forests. In principle, approaches like forest comanagement have the potential to respond to this double objective. Nonetheless, there remains a need for additional evidence regarding the effects of such programs on both the well-being of local communities and on conservation efforts.

Chapter 2

Forest Co-management and Poverty-Environment Traps

co-written with Charles Palmer (LSE)

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Abstract

Implemented globally since the 1990s, co-management involves the devolution and transfer of common-pool resource rights from governments to rural communities. In practice, this process often also involves efforts to improve households' returns to labor with respect to resource extraction and production. Quantitative empirical evidence to date suggests mixed effects with respect to forest co-management's impacts on poverty and resource conservation, including in Sub-Saharan Africa. Our study seeks to contribute to the literature with a better understanding of the behavioral channels through which co-management influences poverty and forests and the mechanisms by which co-management changes behavior underlying outcomes. With a focus on Malawi, we construct a household panel dataset and empirically evaluate the poverty and forest impacts of the national-level Improved Forest Management for Sustainable Livelihoods Programme (IFMSLP) two and five years after it ended in 2014. The results from application of a difference-in-differences framework to our data suggest that the IFMSLP increased rather than reduced household poverty. As measured by incomes, assets and a measure of food security, the Food Consumption Score, the estimated increase in poverty is larger in 2016 than in 2019. The IFMSLP had no overall effect on deforestation. To understand why and how co-management increased poverty, we test the hypothesis that co-management's focus on resource extraction and use, coupled with fewer alternative livelihood options, is associated with lower labor productivity and hence, worsening poverty. The increase in poverty is found among households with fewer livelihood options and a dependence on subsistence agriculture and fuelwood collection prior to co-management.

2.1 Introduction

Over 1 billion people globally derive direct and indirect benefits from forests in the form of employment and the contributions of timber and non-timber forest products to livelihoods and incomes (Angelsen and Wunder, 2003, Angelsen et al., 2014, Wunder et al., 2014a). Dependence on forest products to meet nutritional, energy and housing needs facilitated growth in the design and implementation of policies by governments and other stakeholders to support livelihoods and incomes, alleviate poverty and conserve natural resources (Shyamsundar et al., 2020). Where common-pool resources are claimed and utilized by local user groups or communities, a popular policy implemented widely since the 1990s has been the co-management of resources between governments and communities. Co-management typically involves the devolution and transfer of rights to access, use and manage common-pool resources from governments to communities, in many cases formalizing aspects of pre-existing *de facto* common property regimes (Ostrom, 1990, Baland and Platteau, 1996, Engel et al., 2013, Mansuri and Rao, 2013). Almost 30% of forests located in low- and middle-income countries are currently legally owned or managed by local communities (Rights and Resources Initiative, 2018). Transferring and formalizing resource rights, in principle, improves local access to and management of resources, potentially motivating effective cooperation in the management and protection of resource stocks and flows of benefits to communities (Robinson et al., 2014, Palmer et al., 2020). In practice, co-management often also involves implementing activities designed to improve livelihoods and households' returns to labor with respect to resource extraction and production. The potential for co-management to reduce poverty and conserve resources has, in many settings, reportedly not been realized. Yet, much of the existing evidence with respect to forest co-management's impacts on both poverty and conservation is based on case studies, small samples, or surveys of geographically narrow areas and hence, causal inference is limited (Hajjar et al.,

2021, Miller et al., 2021). The relatively small number of studies adopting a program evaluation approach typically estimate either poverty or forest outcomes, and provide little or no empirical evidence of the behavioral channels through which co-management influences poverty and forests and the mechanisms by which comanagement shapes behavior underlying outcomes. However, a recent study by (Libois et al., 2022) presents compelling incentives to delve deeper into understanding these behavioral pathways. Specifically, in exploring the underlying mechanisms behind the improvement of forests resulting from community forest management in Nepal, the authors offer interesting insights into changes in household behavior with respect to energy choices. Their examination of changes in household behavior, which are tightly linked to the use of firewood, opens avenues for further exploration of the links between poverty and conservation within the framework of such interventions. This being said, previous research undertaken at the household scale suggest mixed effects, including in Sub-Saharan Africa, and heterogeneous effects within co-management schemes, e.g., in Malawi (Jumbe and Angelsen, 2006); in Ethiopia (Gelo and Koch, 2014, Mazunda and Shively, 2015), and Tanzania (Pailler et al., 2015, Keane et al., 2020). Focusing on both poverty and forest outcomes, we expand the evidence base, and our understanding of what drives co-management's outcomes, with a program evaluation of a national-level forest co-management scheme in Malawi, the Improved Forest Management for Sustainable Livelihoods Program (IFMSLP).

Implemented in two phases between 2005 and 2014, the granting of legal rights to forest resources potentially provides the basis for sustainable development in a country where resource-dependent livelihoods and a high incidence of poverty reflect the critical role of forests as a safety net for the rural poor (Jumbe and Angelsen, 2006, Mazunda and Shively, 2015, Meyer, 2023, Mulungu and Manning, 2023). Indeed, the incidence and extent of rural poverty in Malawi implies 'low-hanging fruit' with respect to efforts to alleviate poverty. As detailed in Section 2.2, we focus our program evaluation on phase II, implemented between 2012

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and 2014, when the IFMSLP was scaled up and forest rights were formalized and transferred to communities across the country with the explicit aims of reducing poverty and conserving forests (Olivier and Mwase, 2012, Remme et al., 2015). Communities received legal rights to access, withdraw and manage resources, as well as exclusion rights, in Malawi's protected areas, known as Forest Reserves (FR), and in areas of land customarily claimed by communities outside the Reserves.¹

First, we evaluate the impacts of the IFMSLP on three measures of poverty: a measure of food security, the Food Consumption Score (World Food Programme, 2008), assets, and incomes, proxied by non-food expenditures. Our measures are chosen to reflect the multi-faceted nature of poverty. They are also closely related to one another, to the extent that we would anticipate consistency in our results in terms of the direction of effect. Thus, income is typically either saved, generating assets, or consumed. Consumption expenditures include food expenditures but in the context of resource-dependent livelihoods, food can also be collected from forests, or grown. Food from any source is necessary for labor productivity, which in turn influences incomes, consumption and savings (Banerjee and Duflo, 2011). Second, we evaluate the extent to which the IFMSLP achieved forest conservation, which we interpret, at the minimum, as zero-gross deforestation within the range of the time it takes for households to collect fuelwood, an activity that was commercialized under the IFMSLP in the form of Forest Based Enterprises (see Section 2.2).

We construct a panel dataset, described in Section 2.3, from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture, specifically four rounds of longitudinal household data (2010, 2013, 2016, 2019) from the Integrated Panel Household Surveys for Malawi, combined with spatial data on Malawi's Forest Reserves and annual data on forest loss from the Global Forest Change dataset (Hansen et al., 2013). To infer a causal relationship between the

¹Although formal ownership rights to forest land were not transferred, communities often felt a greater sense of ownership to customary land than land co-managed in Forest Reserves (Remme et al., 2015).

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IFMSLP and its impacts on poverty and forests, we create a control group comprising households resident in communities that were not selected into the IFMSLP. However, there is no information on how communities were selected to participate in the IFMSLP. Likely selection bias is addressed by application of a difference-indifferences framework combined with a Propensity Score Matching (PSM). This approach is further justified given the large differences between our treated and control groups, namely that the former were poorer and lived in remoter areas with higher forest cover than the latter. Specifically, in an attempt to narrow these differences, we match households on the basis of: household size, livestock ownership, the value of durable assets, food expenditures, distance to the closest population center, elevation and forest cover. Our results remain robust to different combinations of matching variables.

Our findings for the policy outcomes, presented in Section 2.4, suggest that the IFMSLP did not succeed in achieving its poverty goals, instead leading to reduced food security, non-food expenditures, and assets in 2016. By 2019, these negative impacts had mostly dissipated, but not reversed. The absence of an observable effect on deforestation suggests that the IFMSLP, broadly speaking, met its forest conservation goal. Our household sample is subsequently examined for possible biases. First, we remove households resident in Lilongwe district from the control group. That Malawi's capital city is located in this district could bias our results downwards if access to the capital provides, e.g. labor opportunities, unavailable elsewhere. Second, although we already removed from our sample households that moved and hence, switched treatment status over time, we reinstate these households and run the heterogeneity-robust estimator (De Chaisemartin and D'Haultfœuille, 2020). The results from these two checks are again consistent with our main results.

Another possible challenge to identification concerns our lack of pre-treatment trend data. The parallel trends assumption is checked using survey data collected in 2010 and 2013. Although phase II began in 2012, forest rights were transferred

to most if not all communities in 2013 and 2014 (Remme et al., 2015). Namely, these rights aim to grant communities legal authority to manage and utilize forest resources on Malawi's state-owned land. Additionally, under the terms of a formal agreement with the Director of Forestry, targeted communities are authorized to issue licences to extract forest products and generate revenue from diverse forms of usage (Remme et al., 2015). To validate the use of 2013 data as a check on common trends, we re-run the DiD estimator using 2013 outcomes as a kind of placebo test. Results are suggestive of a weak treatment effect in contrast to those for 2016 and 2019. Thus, we estimate the average treatment effect on the treated after conditioning on covariates via application of the doubly-robust estimator (Sant'Anna and Zhao, 2020) to our data. The results of this estimator are in line with our main results. We next check the validity of our treatment areas, assumed to be located between 5 km and 20 km from Forest Reserve boundaries (Olivier and Mwase, 2012). To account for a maximum 5 km 'random location offset' with respect to households' locations, we check the maximum reach of the treatment areas by adjusting their furthest extent, 15 km and 25 km from Reserve boundaries. We also amend the locations of the treatment areas, first, 0 and 5 km and second, 25 km to 40 km from Reserve boundaries. The 0-5 km areas capture households that were treated in phase I (2005-2009) while the 25-40 km areas capture households that were never treated. Next, we run a placebo test to ensure that our outcomes are driven by the IFMSLP and not some unobserved event. In our case, Malawi's 2015-16 drought had a critical impact on food production and security (McCarthy et al., 2021, e.g.,). We thus re-run our DiD estimator using values of the Standardized Precipitation Evapotranspiration Index (SPEI) as outcomes instead of our policy outcomes, among other tests. Finally, to ensure that our results are not biased by a follow-up policy to the IFMSLP, the PERFORM project, we remove from our sample the three districts in which this project was implemented between 2014 and 2019. Results from all of these checks are consistent with our main results.

That the IFMSLP appears to increase rather than decrease poverty raises ques-

tions regarding why and how. The IFMSLP's focus on resource extraction and use, facilitated by the transfer and formalization of forest rights, is hypothesised to be associated with lower labor productivity and hence, worsening poverty. In Section 2.5, we first establish that the increase in poverty due to the IFMSLP is primarily occurring amongst households that were already resource dependent and either unable to access, or engage with, alternative livelihoods and income-earning opportunities. Specifically, we examine the point estimates depending on whether households, in 2010, engaged in different livelihoods and income-earning opportunities. Households found to be worse off as a result of the IFMSLP are mostly those that had limited labor alternatives, and were already largely dependent on subsistence agriculture and fuelwood collection for their livelihoods and incomes.

Given that households dependent on fuelwood collection or subsistence farming become poorer due to the IFMSLP, we then ask how co-management made households poorer. Increased poverty implies a reduction in the households' returns to labor with respect to fuelwood collection and subsistence farming. The transfer of access and withdrawal rights suggests the possibility of greater benefits to households extracting and using resources, while the transfer of management and exclusion rights to communities implies the potential for higher costs from extraction. A reduction in a household's returns to labor therefore implies that any additional benefits are outweighed by additional costs imposed by co-management. Yet, any additional costs or benefits depend on the configuration of forest rights determining the costs and benefits of household resource extraction prior to comanagement. The *de jure* status quo configuration of rights implies greater net benefits from extraction in customary areas compared to Forest Reserves, where extraction is prohibited. However, de facto rights are likely to differ from de jure rights (Olivier and Mwase, 2012, Remme et al., 2015, Kamoto et al., 2023). The former are not observed but higher costs and hence, lower returns to labor, could be generated when households with *de facto* rights to extract face greater restrictions due to the transfer of management and exclusion rights to communities (Angelsen,

2007)². As highlighted by (Lokina and Robinson, 2008), within the framework of Joint Forest Management (JFM) initiatives, while these programs may assign communities the responsibility of protecting forest ecosystems and bearing associated costs, they may also entail the loss of their existing *de facto* rights to harvest NTFPs such as fuelwood and other resources (Kajembe and Nzunda, 2002, Lovett, 2003, Mertz et al., 2005). A rational household facing lower returns to labor could attempt to switch to alternative income-generating activities. Where alternative income-generating activities are either unavailable or inaccessible then the household might have little option but to continue extracting resources even though it is likely to be sub-optimal for the household to do so (Delacote, 2009, Barbier, 2010, Barbier and Hochard, 2019).

To locate the source of the negative effects of the IFMSLP, Section 2.6 examines spatial variation in impacts by repeating the analysis of Section 2.4 at the regional scale. Thus, we estimate the poverty and forest impacts of the IFMSLP in the Central and South regions, two broadly comparable regions from a biophysical and economic perspective. The results suggest that the increase in poverty is concentrated in the Central region, with no effect estimated in the South. We also find some evidence of an increase in deforestation in the Central region but again no evidence of an effect in the South. As expected, the differences in terms of impacts conditional on the allocation of household labor are, overall, more pronounced in the Central compared to the South region.

The results of our study, discussed in Section 2.7, contribute to three strands of literature. First, the application of program evaluation methods to forest comanagement typically either focuses on poverty (e.g., Pailler et al., 2015) or forest (e.g., Chankrajang, 2019) outcomes, but not both. Given co-management's emphasis on resource use and extraction, a focus on one or other outcome overlooks

²Management rights included the authority to design and charge licence fees to households extracting resources. Collected fees were supposed to help finance the costs of running the comanagement institutions established by the IFMSLP. Case study evidence suggests, however, that fees were often punitive and infrequently collected (Olivier and Mwase, 2012, Remme et al., 2015, Kamoto et al., 2023)

the high likelihood of a close relationship between human well-being and the local environment (see e.g., Lade et al., 2017). Amongst the few relevant studies that evaluate both poverty and forest outcomes, (Mazunda and Shively, 2015) examined the effects of participation in Malawi's Forest Co-management pilot project, a precursor to the IFMSLP, on household incomes and forest. They found positive forest outcomes but no change in incomes, although these effects were estimated using a control group of non-participating households located in treatment areas. Hence, the effects could be biased due to households free-riding on the benefits of co-management and other spillover effects. Oldekop et al. (2019) evaluate the poverty and forest impacts of a national co-management scheme in Nepal at the sub-district scale, finding positive poverty and forest outcomes. Although their control group was not exposed to the treatment, the scale of their unit of analysis precludes further empirical analysis with respect to the reasons as to why they find positive outcomes. More generally, behavioral channels and mechanisms of effect, where discussed in previous studies, have, to our knowledge, neither been theoretically investigated in an economic framework nor empirically evaluated. Our analysis of the household's labor allocation decision in the context of co-management thus contributes to our understanding of what drives co-management outcomes.

Second, our study sheds light on the extent to which a policy that emphasizes support to resource extraction and the generation of 'environmental income' contributes to lifting people out of poverty. Natural resources can make important contributions to livelihoods, specifically as a source of products for own consumption (subsistence). Resource dependence and subsistence can prevent further poverty yet low returns from non-subsistence extraction due to, e.g. lack of scale, low labor productivity, and missing markets, is likely to be insufficient to alleviate poverty (Angelsen and Wunder, 2003). At worse, there is potential for a poverty trap, defined as self-reinforcing cycles of poverty (Jalan and Ravallion, 2002, Barrett et al., 2011, Kraay and McKenzie, 2014, Barrett et al., 2016). To date, however, there is little evidence that reliance on environmental income generates poverty traps nor evidence that environmental income contributes to rural households' overall asset accumulation, as demonstrated in, e.g., Nepal (Walelign et al., 2021). Our study shows how policies which facilitate a reliance on environmental income could, in the absence of viable alternative income-generating activities, potentially worsen poverty, at least in the short-term.

Third, although we find no evidence of an asset-based poverty trap, we do find suggestive evidence in the Central region of a poverty trap involving resource use, dependence and degradation. So-called poverty-environment traps have been found to be largely geographically determined, that is, where marginal agricultural land and forests are prevalent (Delacote, 2009, Barbier, 2010, Barbier and Hochard, 2019). Such traps have also been used to characterize settings where access to markets and infrastructure is lacking, all of which constrain the ability of poor households to improve incomes and livelihoods (Jalan and Ravallion, 2002, Barrett et al., 2011, Kraay and McKenzie, 2014, Barbier and Hochard, 2019). Our analysis suggests that labor markets play a key role, not only in providing alternatives to resource extraction when the returns to labor fall, but also in preventing continued dependence on the local resource base for livelihoods and the potential for forest loss. The critical role of alternative labor opportunities has been explored theoretically, in a context of imperfect or missing markets for labor (e.g., Angelsen, 1999), and empirically, e.g., off-farm labor opportunities as a way for households to overcome potential trade-offs between rising incomes and declining forest (Zwane, 2007). Our study is, to our knowledge, the first to empirically demonstrate at the household scale, how the timing and magnitude of increases in poverty and deforestation might be linked to a dependence on resource extraction and the extent of outside options for a rural household's labor supply.

2.2 Background

Rural incomes and livelihoods in Malawi are heavily resource dependent. The primary livelihood activities of the rural poor typically include own-farm production, fuelwood and water collection, and casual off-own-farm labor known as ganyu. Undertaken by men, women and children, on behalf of relatives and neighbors as well as other farmers, ganyu is widespread in Malawi (Bouwman et al., 2021). Common ganyu tasks include land preparation prior to the growing season (ridging) and weeding during the growing season, usually undertaken as piecework, paid in cash or in kind (Whiteside, 2000). After own-farm production, ganyu is the most important livelihood strategy of rural households (Whiteside, 2000, Coulibaly et al., 2015), particularly for those with smaller land holdings unable to meet their consumption needs through own-farm production (Mtika, 2001, Holden, 2014). Ganyu can also function as an insurance mechanism and a safety net (Whiteside, 2000, Michaelowa et al., 2010). By taking households away from tending their own plots, there might be delays in, e.g., planting and weeding, possibly impacting on yields, although this negative effect on welfare has been shown to be offset by the diversification of household livelihood strategies (Orr et al., 2009).

Tree cover in Malawi fell from 16% in 2000 to 13% in 2020, with agricultural conversion and the demand for fuelwood and charcoal identified as the main drivers of deforestation and forest degradation (e.g., Jagger and Perez-Heydrich, 2016, Abman and Carney, 2020). Like many countries around the world, Malawi's government began the process of devolving forest management in the 1990s. In Malawi's case, the process started with the National Forest Policy (1996) and Forest Act (1997) leading to the National Forest Program, launched in 2001 (GoM (Government of Malawi), 1996, 2003). This process effected a shift from unambiguous forest protection towards a more participatory approach to forest management, also termed participatory forest management in Malawi. In 1996, the Forest Comanagement program was piloted by Malawi's Government in two protected areas,

known as Forest Reserves.

With the caveat that households in the control group resided in treatment areas, Malawi's co-management pilot program has been shown to have a positive impact on incomes in 2002 (Jumbe and Angelsen, 2006), which had largely dissipated by 2009 (Mazunda and Shively, 2015). Building on the pilot program but scaled up nationally, the devolution process culminated with the IFMSLP. Implemented by Malawi's government in 12 districts over two phases (2005-2010 and 2012-2014), and with €18.8 million of financial support provided by the European Union, the stated goals of the IFMSLP in phase I were to increase household incomes and improve food security through sustainable forest management (Olivier and Mwase, 2012). In phase II, these goals were subsumed under a broader aim of poverty reduction and augmented with a new aim of forest conservation (Remme et al., 2015).

In a context of unclear tenurial and usufruct arrangements, the IFMSLP provided communities with legal rights to co-manage and harvest forest products on state land through co-management agreements negotiated with Malawi's Department of Forestry (Kamoto et al., 2023). Communities received legal rights to access, withdraw and manage resources, as well as exclusion rights, in areas of land known as 'blocks' in Malawi's protected areas (Forest Reserves), and in areas of land customarily claimed by communities outside the Reserves known as 'village forest areas'. Key to legalizing forest exploitation was the formulation and formalization of Forest Management Plans. Although the final total is disputed, perhaps over 200 Plans, typically one per community, were established by the end of phase I in 2009 (Olivier and Mwase, 2012). Yet, most of these Plans were only finalized and formalized at the end of phase II, in 2013 and 2014, ending a process that not only involved development of the Plans but also institution building, participatory forest resource assessments, Sustainable Livelihood Analysis, Monitoring and Evaluation, and support to Forest Based Enterprises (Olivier and Mwase, 2012, Remme et al., 2015). Almost 400 Forest Based Enterprises were established during phase

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I to support local livelihoods and incomes, including fuelwood collection and sale, timber and non-timber forest products, such as mushroom and honey production, and the establishment of tree nurseries. Yet, most Forest Based Enterprises became dormant between the end of phase I and start of phase II, reportedly due to inadequate access to markets and low levels of production (Remme et al., 2015). The IFMSLP also provided opportunities for wage labor via the construction and maintenance of firebreaks in forest areas.

Co-management activities were allowed to take place in designated areas within 18 so-called Impact Areas established during phase I. These Impact Areas comprised Forest Reserves and their surrounding buffer zones, which typically included customary areas claimed and utilized by communities selected to participate in the IFMSLP. Co-management activities during phase I were restricted to households resident in communities with customary land claims in buffer zones within 5 km of the borders of Forest Reserves (Olivier and Mwase, 2012). Within these buffer zones, Forest Management Plans and co-management activities were piloted during phase I, alongside capacity building of frontline staff working for the Department of Forestry. Activities in phase II continued in the same Impact Areas as in phase I except that the buffer zones and hence, the beneficiary-catchment areas, moved from 5 km to 20 km from Forest Reserve boundaries in an effort to scale up and expand participation among communities with customary land claims.

Legal rights were transferred to communities for accessing, using and managing designated forest areas in the Impact Areas. Emphasis appeared to be placed on the sale of firewood and non-timber forest products, for which licence fees were charged to help finance the costs of running the co-management institutions established by the IFMSLP (Kamoto et al., 2023). Yet, case study evidence, e.g., Zulu (2013), suggests that with licence fees accounting for over 50% of gross revenues, some groups set up for commercial fuelwood production made relatively little profit and were abandoned after a single harvesting season. Other case studies suggest that fuelwood production, alongside charcoal and timber production, and agricul-

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tural conversion, may have expanded illegally in Impact Areas, e.g., by community members not paying licence fees, leading to forest degradation and increased time needed to collect forest resources (e.g., Senganimalunje et al., 2015, 2016).

We focus our program evaluation, that is, our treatment period, on phase II, when, building on phase I, co-management was scaled up in all 18 Impact Areas. the majority of Forest Management Plans were finalized and communities' forest rights were formalized. Although the objectives of the IFMSLP changed between phase I and II, the policy approach remained the same. As such, the aim of poverty reduction in phase II is assumed to encompass the more specific aims related to incomes and food security in phase I. The treatment in our program evaluation focuses on the expansion of legal rights to access, use and manage forest resources, and exposure to opportunities to participate in Forest Based Enterprises. It is important to note that two impact areas are not included in our study due to the absence of precise GPS coordinates of their locations - we thus remove from our sample the districts within which they are located³. Moreover, after the conclusion of the IFMSLP in 2014, the Protecting Ecosystems and Restoring Forests in Malawi (PER-FORM) project was implemented in the Forest Reserves of Perekezi, Ntchisi, and Liwonde in the Mzimba, Ntchisi, Machinga districts, respectively, between 2014 and 2019. The purpose of PERFORM was to 'consolidate and improve the legacy of the IFMSLP' (Kamoto et al., 2023). As such, by removing these districts from the sample we perform a robustness check to ensure that the implementation of PERFORM does not bias our results.

³These include the Chawa proposed Forest Reserve in the Kasungu district and the Masenjere Escarpment in the Chikwawa district.

2.3 Data and methodology

2.3.1 Data

2.3.1.1 Household and forest data

Household-level data is derived from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). Specifically, we use the Integrated Household Panel Surveys (IHPS) for Malawi across four survey rounds: 2010, 2013, 2016 and 2019. The household sample expanded each survey round via the tracking of both original and split-off households. Hence, the panel sample, which comprised 1,619 households during the first survey round, enlarged to 3,178 households in the fourth round (2019) of the IHPS, while maintaining a 5.6 attrition rate (World Bank, 2019).

Data on the condition of forests is derived from the Global Forest Change dataset by Hansen et al. (2013). This database provides information on global forest cover and change over the period 2000 to 2021 at a spatial resolution of approximately 30m per pixel at the equator. In this analysis, we mobilize the dataset's *Tree canopy cover for year 2000*, which provides the percentage forest cover in the year 2000 (ranging from 0 to 100%), and *Year of gross forest cover loss event*, which detects whether forest was lost in a specific year between 2000 and 2021. Forests are defined as vegetation that is taller than 5 meters in height, and forest loss as a "standreplacement disturbance, or a change from a forest to non-forest state" (Hansen et al., 2013).

We use the FAO's definition of forests to characterize pixels as either forested or non-forested in the forest cover layer. The FAO defines forests as "land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds *in situ*" (FRA, 2020). Therefore, only pixels for which forest cover in 2000 was greater than 10% was kept in

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the tree cover layer. The former was employed as a mask layer to filter the tree loss data, ensuring that the tree loss layer exclusively comprises pixels identified as forested in 2000. Subsequently, we formulate a measure for gross forest loss by quantifying the number of pixels within a specific area and year identified as deforested relative to the count of pixels within the same zone classified as forested in the year 2000. Since rural households typically collect fuelwood, timber and non-timber forest products on foot, it is likely that many households gather forest resources as close to their dwellings as possible, where forests are likely to be fragmented rather than contiguous. Hence, our choice of a minimum tree cover threshold of 10% is also based on the possibility that increased access to such forest areas could lead to over-harvesting and, potentially, further degradation and deforestation.

2.3.1.2 Forest Reserves

Data pertaining to Malawi's Forest Reserves was originally sourced from the country's Ministry of Forestry and Natural Resources website⁴ (now known as the Ministry of Natural Resources and Climate Change Malawi). This was facilitated by the accessibility of a range of geospatial information, including shapefiles on the country's roads, rivers, and protected areas, alongside other datasets. To evaluate the poverty and forest impacts of the IFMSLP, we first differentiate between households that had participated in the IFMSLP in phase I and phase II from those that had participated in phase II only. Thus, we identify all of the Forest Reserves selected for inclusion in the program and create a 20 km buffer around these Reserves, corresponding to the maximum extent of the beneficiary-catchment area established during phase II, the Impact Areas of the IFMSLP. Subsequently, we deduct a 5 km area from the Reserves' borders to exclude households residing within 5 km of the FR boundaries in Impact Areas. This exclusion aims to eliminate the catchment areas covered in phase I, which extended only up to 5 km (Olivier and

⁴https://mnrcc.gov.mw/

Mwase, 2012), ensuring a clear baseline. Households located between 5 km and 20 km from the treated FR are retained in our treatment group.

To establish our control group, we generate identical 20 km buffers around the Forest Reserves⁵ not chosen for inclusion in the IFMSLP. Additionally, we exclude areas within 5 km of the Reserve borders to ensure comparability between the locations of treated and non-treated households. Next, we overlay our EAs on to the Forest Reserve polygons. The process is repeated for each survey year, taking care to remove polygon areas that overlap to ensure that no EA in the control group is located within a treated area. As a result, our treated group is located at a distance of 5 km to 20 km of a Reserve selected into the IFMSLP, while our control group is located at a distance of 5 km to 20 km distance of a Reserve that was not included in the program⁶. Figure 2.1 shows the location of the Forest Reserves included in our analysis, distinguishing between those that were part of the IFMSLP from those that were not. Moreover, it shows the location of both our treated and non-treated

EAs.

⁵These include a few proposed Forest Reserves.

⁶For robustness, and given that for reasons of confidentiality the GPS coordinates of surveyed households include a random offset of precise EA coordinates by distances ranging from zero to two kilometers in urban areas and two to five kilometers in rural areas, with a displacement of up to ten kilometers for one percent of rural regions (Blankespoor et al., 2021), we also conduct the analysis using 15 km and 25 km buffers to see how the treatment effect evolves with various distances.

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Figure 2.1: Location of treated and non-treated EAs

2.3.2 Outcome measures

To evaluate the impact of the IFMSLP on poverty, we adopt three different measures: food security, assets, and a proxy for household incomes, non-food expenditures. Not only does the adoption of these measures collectively attempt to capture the multi-dimensional nature of poverty at the household level but they are also inter-connected via the household's labor supply and consumption decisions. This implies that any impacts estimated due to the IFMSLP are expected to move in a similar direction regardless of the measure used. For example, an increase in incomes due to the IFMSLP is expected to lead to higher savings, potentially gen-
erating assets, or more consumption. Productive assets could contribute to future incomes while higher consumption expenditures could be allocated to food or nonfood items. The quantity and quality of food consumed influences labor productivity, which in turn, impacts the household's labor supply decisions, including the amount of time a household allocates to own-food production and food collection in the commons, all of which contributes to household incomes and well-being.

2.3.2.1 Food security

Given that co-management allows for the legal extraction of forest products both for own-consumption and for commercialization and sale, a food security measure is a useful indicator of household well-being. We employ the Food Consumption Score (FCS), introduced by the WFP in 1996, which is designed to gauge both the variety and nutritional content of the food groups consumed by a household over the past seven days, as well as the frequency of consumption during this period (World Food Programme (WFP), 2008). As detailed in World Food Programme (WFP) (2008), the score is calculated by consolidating the consumption frequencies of eight different food groups, and multiplying these frequencies by a standardized weight determined by the nutrient density of each respective food group (see Appendix A.2).

2.3.2.2 Value of assets and weekly expenditures

To test the extent to which the IFMSLP has affected the level of wealth and consumption of households, we mobilize a measure of current asset value and nonfood expenditures within each household. First, the value of assets is computed by summing the reported values associated with the durable goods owned by the household, such as tables, chairs, beds, televisions, air conditioners, refrigerators, bicycles, and so on. The latter measure is adjusted for inflation, expressed in logarithmic form, and in Malawian Kwacha (MWK). Secondly, we develop a metric

for non-food expenditures, encompassing all household expenses from the preceding week, including purchases such as charcoal, paraffin or kerosene, cigarettes, matches, candles, newspapers, and transportation (such as bicycle taxi, bus, and other means), which reflect fundamental needs like energy and mobility. This variable is represented in real terms, presented logarithmically, and denoted in Malawi's national currency.

2.3.2.3 Forest loss

Previous research indicates a decline in forest resources attributed to increased extraction (legal and illegal) and reports of increased time needed for communities to collect resources in IFMSLP Impact Areas (Kamoto et al., 2023). To examine how the IFMSLP might have affected forest cover via the availability of forest resources, we develop a measure of forest loss based on the time household members spent walking from their residences to firewood collection sites at baseline. Specifically, we establish several buffer zones around household Enumeration Areas (EAs) based on firewood collection times, assuming an average walking speed of 10 minutes per kilometer. Within each buffer, we calculate the percentage of forest loss in the year preceding the survey⁷ for each zone. Therefore, e.g., if members of a particular household in 2010 reported walking 60 minutes to reach the location where they collect firewood, we create a buffer of 6 km around the EA, with an additional 5 km added to account for household location offsets, before assessing the extent of forest loss within this area. We repeat this procedure for the reported collection times of each household. Additionally, our analysis is based on firewood collection times reported in 2010. Thus, in the context of the forest loss analysis, we confine our sample to households that remained within 10 km of their original location (as reported in 2010) in both 2016 and 2019.

⁷Survey questions pertain to household activities conducted in the 12 months preceding the questionnaire.

2.3.3 Descriptive statistics

A comparison of the treated and control groups reveals several key differences, as reported in Tables 2.1 and 2.2⁸. Notably, treated households are more likely than control households to own livestock, to be more asset-deprived, spend less money on food, and live in more remote areas, that is, areas with higher forest cover (in 2010). Although not explicitly presented in these tables, significant statistical disparities are also observed in two of our outcome variables: assets and non-food expenditures, across both the 2010-16 and 2010-19 samples. Collectively, households in the treated group demonstrate greater economic vulnerability compared to the control group. Nevertheless, the tables below illustrate that the matching conducted at baseline effectively mitigates these discrepancies between the two groups. The detailed empirically strategy is presented in the next section.

⁸These covariate balance tables only pertain to the measures of the FCS and the value of durable goods (in log). The tables for non-food expenditures, both for 2016 and 2019, are in Appendix B.2.

	Unmatched (U)	Mean		Bias	as t-test	
	Matched (M)	Treated	Control	%	t	p> t
Variables						
Household size	U	5.3568	5.3499	0.3	0.04	0.971
	Μ	5.3568	5.2532	4.4	0.45	0.655
Livestock ownership (1=ves)	U	0.60302	0.46537	27.8	3.50	0.000
	Μ	0.60302	0.62029	-3.5	-0.35	0.724
Asset value (log, real terms, MWK)	U	8.2342	9.0272	-42.5	-5.26	0.000
	Μ	8.2342	8.2372	-0.2	-0.02	0.986
Food expenditures (log, real terms, MWK)	U	6.7357	7.2488	-43.8	-5.12	0.000
	Μ	6.7357	6.6528	7.1	0.74	0.460
Distance to pop. center (km)	U	32.978	27.009	31.9	3.89	0.000
	Μ	32.978	34.995	-10.8	-1.08	0.279
Forest cover (%) - 10 km buffer	U	16.397	12.903	55.0	6.04	0.000
	Μ	16.397	16.239	2.5	0.22	0.829
Elevation (m)	U	912.35	1002.3	-26.9	-4.14	0.000
	M	912.35	943.27	-9.2	-0.88	0.378

Table 2.1: Balancing test - FCS & assets, 2016

Notes: The outcome for which these covariates are matched are the FCS and the value of durable goods (log). The number of untreated and treated households is of 823 and 199 respectively after matching.

	Unmatched (U) Mean		Bias	t-test		
~	Matched (M)	Treated	Control	%	t	p> t
Variables						
Household size	U	5.4809	5.4406	1.7	0.24	0.811
	Μ	5.4809	5.3812	4.3	0.45	0.651
Livestock ownership $(1=yes)$	U	0.61702	0.45573	32.7	4.48	0.000
	Μ	0.61702	0.61906	-0.4	-0.05	0.964
Asset value (log, real terms, MWK)	U	8.2128	8.9868	-41.8	-5.63	0.000
-	М	8.2128	8.1268	4.6	0.53	0.594
Food expenditures (log, real terms, MWK)	U	6.712	7.2588	-47.4	-6.06	0.000
	Μ	6.712	6.6074	9.1	1.01	0.312
Distance to pop. center (km)	U	33.059	27.234	31.0	4.11	0.000
	М	33.059	35.521	-13.1	-1.37	0.173
Forest cover (%) - 10 km buffer	U	16.627	12.68	63.2	7.60	0.000
	Μ	16.627	16.347	4.5	0.44	0.663
Elevation (m)	U	908	996.58	-27.1	-4.54	0.000
	Μ	908	940.58	-10.0	-1.03	0.303

Table 2.2: Balancing test - FCS & assets, 2019

Notes: The outcome for which these covariates are matched are the FCS and the value of durable goods (log). The number of untreated and treated households is of 994 and 235 respectively after matching.

2.3.4 Empirical Strategy

Our analysis seeks to establish a causal relationship between the second phase of the IFMSLP and its impact on households residing within or in close proximity to the program's Impact Areas. To achieve this objective, we employ a difference-indifferences approach, utilizing data from the 2010 household survey as our baseline year. We estimate the overall program impact in 2016 and 2019, respectively, representing two and five years after the conclusion of IFMSLP phase II in 2014.

Furthermore, to compare our treated and non-treated households while preventing bias that may result from disparities in the characteristics between both groups, we combine our DiD model with Propensity Score Matching (PSM). The PSM method permits to compute, via a logit or probit model,⁹ the probability of being in the treatment group based on a set of observable characteristics (Caliendo and Kopeinig, 2008). Specifically, we use a Kernel matching (with a bandwidth of 0.01), which is a non-parametric matching estimator that constructs the counterfactual by using the weighted averages of all untreated households (Caliendo and Kopeinig, 2008). In this study, the observed household and EA attributes mobilized to conduct the PSM are the following: household size (count); livestock ownership (1=yes); value of durable assets (log, real terms, MWK); food expenditures in the past week (log, real terms, MWK); households' distance to the closest population center (km); elevation (m); average forest cover in an area of 10 km around EAs (%). The matching is conducted at baseline, before the onset of phase II of the IFMSLP, in order to minimise selection bias. Our results remain robust to different combinations of matching variables.

Moreover, we exclude households from our sample that underwent a change in treatment status over time due to relocation. Given that some households relocated between 2010 and 2016/2019, this resulted in a subset either entering or

⁹In this analysis, a probit model is used to estimate the propensity score. The propensity score estimated via a logit model yields similar results.

exiting treated areas between the initial baseline and subsequent survey rounds¹⁰. Following this adjustment, 458 households are classified as treated and 1,888 as untreated in the 2010-2016 sample, while 546 households are treated and 2,288 are untreated in the 2010-2019 sample. Our fixed effects model is defined as follows:

$$Y_{it} = \beta_0 + \beta_1 * Treatment_i + \beta_2 * Post_t + \beta_3 * (Treatment * Post)_{it} + \delta_i + \mu_{it} \quad (2.1)$$

where Y_{it} is one of our main outcomes of interest for household *i* at time *t*, which is either the FCS, the value of durable goods (log, real terms, MWK), the value of non-food expenditures in the past week (log, real terms, MWK), or gross forest loss (in %) within the maximum walking range for collecting fuelwood in 2010; δ_i represents the unobserved time-invariant household effect; and μ_{it} is the error term.

The coefficient β_3 represents the treatment effect, our primary focus, and reflects the differences between our baseline period (2010) and the post-treatment period (either 2016 or 2019) across our two groups of households. Additionally, the DiD framework relies on the parallel-trends assumption, which posits that, in the absence of treatment, households within the Impact Areas of the IFMSLP would have experienced similar trends in food security and overall wealth compared to those not affected by the forest co-management program (refer to Appendix B.1 for trends of our main outcomes). Consequently, we employ the DiD framework with weights derived from Kernel matching, allowing us to adjust for unobservable household attributes and ensuring comparability between treated and control households (see Tables 2.1 & 2.2, and Appendix B.2 for covariate balancing tests).

¹⁰Individuals who left the baseline household to establish or join another household in subsequent year(s) might not be situated within a treated area anymore, although they remain linked to the identification number of their original household.

2.4 Results: policy outcomes

In this section, we investigate the effects of the IFMSLP on poverty indicators, including food security, asset value, and non-food expenditures, as well gross forest loss. As detailed in subsection 2.3.2.3, the forest analysis is based on a subset of households that remained near their baseline location. The findings are presented in Table 2.3.

		2	016	2019					
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment	4.862*	-0.00301	-0.0257	0.0149	5.356**	0.0860	-0.0367	0.0104	
	(2.620)	(0.241)	(0.243)	(0.0176)	(2.575)	(0.228)	(0.214)	(0.0197)	
Post treatment	-2.298	0.464***	-0.0250	0.122*	1.102	0.494***	0.0791	0.102*	
	(1.667)	(0.127)	(0.162)	(0.0688)	(1.310)	(0.116)	(0.180)	(0.0547)	
Treatment X Post	-8.142**	-0.403**	-0.809***	-0.00400	-5.392***	-0.393	-0.00945	0.0347	
	(3.062)	(0.191)	(0.286)	(0.0859)	(1.762)	(0.247)	(0.341)	(0.0773)	
Observations	1,794	1,740	1,570	1,086	2,164	2,057	1,905	1,254	
R-squared	0.050	0.013	0.046	0.087	0.016	0.012	0.001	0.125	

Table 2.3: Treatment effect on the policy's outcomes

Robust standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

Our analysis reveals that two years after the conclusion of the IFMSLP in 2014, households within or near the program's Impact Areas experienced significant declines in their FCS, assets' value, and non-food expenditures. Additionally, while not statistically significant, the negative coefficient on forest loss (column 4) suggests a potential reduction in deforestation.

Examining the effects five years post-program conclusion, the treatment remains associated with a decrease in the FCS at a 1% significance level, though at a smaller magnitude (column 5). The impact on assets and expenditures appears to have dissipated over time (columns 6 & 7). Regarding forest loss, the positive coefficient estimated for 2019 (column 8) indicates a shift towards increased deforestation compared to the 2016 estimate. Nonetheless, overall, findings suggest that the program had no discernible impact, implying no substantial change in gross deforestation due to the IFMSLP.

We conduct several robustness checks on our main findings. First, we replicate our DiD model without incorporating weights from the PSM. The results largely align with our primary findings; however, in this scenario, we observe no significant impact on assets in 2016 and no discernible effects across all outcomes in 2019 (see Appendix B.3). Conversely, in Appendix B.4, we expand the set of matching variables by including factors related to community-level basic services and supplementary agricultural data, such as the presence of irrigation schemes and the proportion of agricultural land within a 1 km radius¹¹. The inclusion of these additional variables leads to minimal changes in our results.

Next, we remove households resident in Lilongwe district from the control group (see Appendix B.5). That Malawi's capital city is located in this district could bias our results downwards if access to the capital provides, e.g., labor opportunities, unavailable elsewhere. This change to our sample is found to have little effect on our main results, although with the exclusion of Lilongwe, the negative coefficient on assets in 2016 is no longer statistically significant. Moreover, recent developments in the DiD literature emphasize, amongst other considerations, that static specifications can face challenges when treatment effects exhibit heterogeneity, whether across time periods post-treatment or across units (Roth et al., 2023). This is notably demonstrated by De Chaisemartin and d'Haultfoeuille (2020), Borusyak et al. (2021) and Goodman-Bacon (2021). In light of these advances, we run our main estimations using the heterogeneity-robust estimator

¹¹The full list of matching variables in these estimations is the following: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), daily market in the community (1=yes), permanent ADMARC (Agricultural Development and Marketing Corporation) market in the community (1=yes), place in the community to purchase common medicines such as pain killers (1=yes), health clinic (Chipatala) in the community (1=yes), post office in the community (1=yes), irrigation scheme in the community (1=yes), community owns a communal forest (1=yes), % under agriculture within \sim 1 km buffer, forest cover (%) - 10 km buffer, elevation (m).

introduced by De Chaisemartin and D'Haultfœuille (2020), which effectively addresses varying treatment effects across households. Furthermore, this estimator permits to account for units that switch in and/or out of treatment. Therefore, within this framework, we reinstate in our sample households with members who either moved away or moved into the household and hence, switched treatment status over time. These results are again consistent with our main results, in terms of the direction and magnitude of effects, but with the negative coefficients for assets and expenditures in 2019 displaying statistical significance.

Regarding our lack of pre-treatment trend data, we first re-run the DiD estimator using the 2013 outcomes. Results are suggestive of a weaker treatment effect on the FCS in contrast to those for 2016 and 2019 (Appendix B.7). In a followup check in case of concerns regarding possible violations of the parallel trends assumption, we estimate the average treatment effect on the treated after conditioning on covariates via application of the doubly-robust estimator (Sant'Anna and Zhao, 2020) to our data (Appendix B.8). The results of this estimator are in line with our main findings, with the negative coefficient for assets in 2019 displaying statistical significance.

The outcomes of these diverse tests appear to validate the reliability of our treatment areas, which are presumed to lie within the 5 km to 20 km range from Forest Reserve boundaries (Olivier and Mwase, 2012). To account for the (maximum) 5 km random location offset with respect to households' locations, we verify the maximum reach of the treatment areas by adjusting their furthest extent, 15 km and 25 km from Reserve boundaries, anticipating effects from the IFMSLP (Appendix B.9). Results once again align with our main results in both 2016 and 2019. We also amend the locations of the treatment areas, first, 0 and 5 km and second, 25 km to 40 km from Reserve boundaries (Appendix B.10 and Appendix B.11 respectively). The 0-5 km areas capture households that were treated in phase I (2005-10) while the 25-40 km areas capture households that were never treated. In both cases, we anticipate no effect from the IFMSLP (phase II). As expected, we

find little or no effect due to the IFMSLP (phase II) thus supporting the location of our treatment areas. Next, we run a placebo test to ensure that our outcomes are driven by the IFMSLP and not some unobserved event. In our case, Malawi's 2015-16 drought had a critical impact on food production and security (e.g., McCarthy et al., 2021). We thus re-run our DiD estimator using values of the Standardized Precipitation Evapotranspiration Index (SPEI) as outcomes instead of our policy indicators, anticipating little or no effect on the outcome. Moreover, as an additional examination, we exclude from our 2010-2016 dataset all observations linked to SPEI values potentially indicative of a weather shock in 2015 or in 2016, and rerun our policy outcomes estimations. We also investigate the effect of the policy on self-reported droughts, instead of the SPEI, both for the 2016 and 2019 samples (refer to Appendix B.12). Results from these checks seem to suggest that our outcomes are not biased by Malawi's drought. Finally, to ensure that our results are not influenced by a follow-up policy to the IFMSLP, the PERFORM project, we remove from our sample the three districts in which this project was implemented between 2014 and 2019. Participation in PERFORM potentially biases the results upwards (less poverty, more forest) (see Appendix B.13). Nevertheless, implementation of the PERFORM project between 2014 and 2019 is found to have relatively little influence on our main results.

2.5 Why did co-management increase poverty?

Having established that the IFMSLP increased rather reduced poverty, an effect that seems to dissipate by 2019, this section examines what might be driving these results. To understand how and why co-management exacerbated poverty, we test the hypothesis that co-management's focus on resource extraction, coupled with engagement with fewer alternative livelihood options, is associated with lower labor productivity and hence, worsening poverty.

2.5.1 Heterogeneous impacts: the household's allocation of labor

To explore sources of heterogeneity based on labor allocation, we segment our sample according to the the various labor activities reported by households at baseline. We specifically examine how the treatment has influenced poverty differently amongst households whose members are exclusively engaged in agricultural labor or firewood collection, compared to households involved in other activities such as non-agricultural work, wage labor, and/or *ganyu* labor. These activities are quantified based on the hours spent by household members in each activity during the preceding week (except for fuelwood collection, which is based on hours spent the day before the survey). Additionally, we explore whether there have been heterogeneous impacts on forest outcomes based on labor allocation using the restricted household sample.

Using the labor variables, we create binary indicators that are assigned a value of '1' if at least one hour was dedicated to a particular labor activity within a house-hold during the specified period, and '0' otherwise. We hypothesize that households with restricted labor options are more prone to experiencing adverse effects from the policy, primarily because of heightened reliance on resource extraction. Such activities typically yield low returns and offer limited potential for poverty allevia-tion when alternative livelihood options are lacking. Hence, we precisely categorize households into three groups based on their labor activities. The first group comprises individuals who spent time collecting firewood the day before the survey, potentially without engaging in farm work, but have not participated in neither non-farm labor, wage labor, or *ganyu*. The second group consists of households where individuals undertook agricultural labor in the week preceding the survey, possibly without collecting firewood the day before, but have not been involved in any other activities. Conversely, the final group includes household members who participated in non-agricultural work, wage labor, and/or *ganyu* labor within the

past seven days but did not engage in neither farm work or firewood collection. The decomposition of the results according to each labor activity is presented in Appendix B.14. To divide the household sample, we use labor values at baseline due to the treatment's potential effect on labor allocation¹². The estimations consist in weighted DiD, using the same matching variables as in Table 2.3, with robust standard errors clustered at the EA level.

¹²Results from weighted DiD indicate that the treatment is associated with a decrease in hours spent on agriculture, both two and five years following the treatment. However, with these estimations we face the challenge of markedly different pre-trends between both groups.





Figure 2.2: Heterogeneous impacts based on labor allocation - 2016



Figure 2.3: Heterogeneous impacts based on labor allocation - 2019

Firstly, concerning Figure B.14.1, which examines the treatment's impact on policy outcomes two years after the conclusion of the IFMSLP's second phase, there seems to be some evidence of heterogeneity in treatment effects based on labor. When examining the food security measure in the upper-left panel, it becomes apparent that households solely engaged in either firewood collection or farm work (or possibly both) are particularly vulnerable to the effects of co-management. For these households, the treatment is associated with a decline in the FCS at statistically significant levels. In contrast, households whose activity portfolio includes non-farm labor, wage labor, and/or *ganyu* labor, while excluding farm work and firewood collection, do not experience any negative impact from the program.

Furthermore, when considering assets as the outcome of interest, in the upperright panel, a similar trend emerges overall. This time, the negative effects are concentrated amongst households engaged in agriculture, and potentially in fuelwood extraction, but not in any of the other labor options. Households with a greater number alternatives, that are not dependent on resource extraction or agriculture, are again not affected by the policy. With respect to the results associated with non-food expenditures as the dependent variable, in the lower-left panel, we observe a negative association between the treatment and expenditures amongst households primarily engaged in firewood collection. Additionally, there is no significant impacts on forest outcomes depending on labor options, as illustrated in the lower-right panel.

Five years after the conclusion of phase II, we observe similar trends as during the previous period when considering households' food security and value of durable goods (see Figure 2.3). In contrast, there are no longer any effects on the level of non-food expenditures. Regarding forest outcomes, while the results are not statistically significant, we can observe a notable trend: the point estimates pertaining to firewood collection and farm work have shifted more importantly towards positive values for forest loss, while the point estimates associated to the other group have remained negative. Overall, the findings illustrated in Figure 2.2 and Figure 2.3 suggest that the effect of co-management varies depending on households' portfolio of labor activities, particularly affecting those with potentially limited labor options at baseline or those already reliant on resource extraction. Furthermore, the results exhibit consistency across our various outcome variables and over time.

2.6 Regional heterogeneity: a comparative analysis

Finally, this section explores whether the program has had any varying impacts across Malawi's regions, which are likely to have specific characteristics with respect to labor opportunities and resource extraction behavior that we do not observe and hence, might not control for in our estimations. Malawi comprises three regions: North, Central, and South. The North is the least-populated region, with fewer urban centres than the other two regions, hilly terrain and an economy based on agriculture and tourism. The Central region is the most-densely populated region, containing the capital city that acts as the country's administrative and commercial hub. Cash crops dominate the rural economy. Cash crops, along with some industrial and mining activities, are also important in the South, a region with Malawi's commercial capital (Blantyre). The South is Malawi's most populous region. We present household and community-level differences at baseline between both regions, and according to treatment status (see Appendix B.15). Disparities between treated and untreated households are most notable in the Central region.

Due to a limited number of observations in the North region, mainly with respect to our treated group, we explore potential heterogeneity between the Central region and the South region only. Estimates of forest loss are conducted using the restricted sample as previously, that is, comprised of households that remained close to their baseline location. Nonetheless, as a robustness check, we also perform the regional analysis on forest outcomes using the full sample and different buffer zones around household EAs (see Appendix B.16).

	2016							
		Ce	ntral		South			
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	2.984	0.235	-0.188	0.0346*	7.279***	0.100	-0.212	-0.00602
	(3.457)	(0.354)	(0.326)	(0.0196)	(2.392)	(0.355)	(0.435)	(0.0219)
Post treatment	-2.469	0.860***	-0.0118	-0.00384	-4.705*	0.215	-0.338	0.198*
	(2.314)	(0.179)	(0.161)	(0.0110)	(2.416)	(0.138)	(0.222)	(0.103)
Treatment X Post treatment	-7.856**	-0.777***	-1.046***	0.132*	-6.136	-0.229	0.203	-0.135
	(3.838)	(0.246)	(0.300)	(0.0631)	(5.216)	(0.297)	(0.244)	(0.103)
Observations	1,014	977	887	578	624	608	561	508
R-squared	0.064	0.019	0.096	0.208	0.066	0.003	0.011	0.131

Table 2.4: Treatment effect by region - 2016

Robust standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

	2016							
		Ce	ntral		South			
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	3.025	0.144	-0.121	0.0180	6.773**	0.297	-0.306	0.00555
	(3.257)	(0.299)	(0.258)	(0.0278)	(2.624)	(0.338)	(0.416)	(0.0288)
Post treatment	-1.163	0.513***	0.311**	-0.0123	2.287	0.455***	-0.431**	0.152**
	(2.121)	(0.186)	(0.145)	(0.0255)	(1.880)	(0.159)	(0.158)	(0.0713)
Treatment X Post treatment	-3.906	-0.521*	-0.365	0.171**	-3.857*	0.0255	0.881**	-0.113
	(2.532)	(0.306)	(0.388)	(0.0703)	(2.233)	(0.402)	(0.318)	(0.0735)
Observations	1,246	1,169	1,084	640	747	720	685	614
R-squared	0.017	0.006	0.009	0.260	0.025	0.029	0.022	0.140

Table 2.5: Tr	eatment effect	by 1	region ·	- 2019
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Robust standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

Firstly, based on Table 2.4, it's evident that two years after the conclusion of the second phase of the IFMSLP, heightened household vulnerability is concentrated in the Central region, while no impact is observed in the South. Specifically, in the Central region, the treatment is linked with a significant decrease in the FCS, asset value, and non-food expenditures. Additionally, there is evidence, although weak,

suggesting an increase in gross forest loss. It is worth noting, however, that there could be concerns regarding the clustering of standard errors in light of the restricted number of observations, and the resulting shrink in the number of clusters, especially in the case of the forest loss estimates¹³.

Regarding the results pertaining to the effect of the treatment five years after the end of phase II, shown in Table 2.5, they reveal that the effects are overall less pronounced, consistent with the findings in Table 2.3, as well as less straight forward. In the Central region, the negative impacts on poverty have generally dissipated. Only a slight influence remains on assets. Nonetheless, the result of increased forest loss persists, and with greater statistical significance. This finding is confirmed in Table B.16.2 of Appendix B.16. When it comes to the South, there is now a statistically significant (10% level), and negative, effect on the FCS. Additionally, co-management is associated with a statistically significant increase in the value of non-food expenditures (5% level), and no effect on forest outcomes¹⁴.

Generally, the regional analysis demonstrates that the IFMSLP has more severely affected households in the Central region. In accordance with the primary findings, the effects on poverty appear to diminish over time. However, this trend does not extend to forest conservation. Notably, the Central region exhibits an increase in deforestation both two and five years after the program's conclusion (with greater evidence in 2019). If co-management encouraged heightened resource use without effectively addressing poverty, particularly in the Central region, individuals may have resorted to increased resource extraction to offset livelihood losses, exacerbating deforestation. This line of reasoning shares some similarities with the scenario outlined in Cardinael et al. (2022) within the context of a REDD+ project. Specifically, the study illustrates a situation where resource conservation did not persist

¹³Removing the standard error clustering in the forest loss model of Table 2.4 column 4, results in a decrease in the p-value below the 0.05 threshold, reinforcing the evidence of a rise in deforestation. As for the forest results in the South (column 8), the absence of clustered standard errors renders the decrease in forest loss statistically significant at a 1% level.

¹⁴In these estimations as well (Table 2.5 column 8) the absence of clustered standard errors results in a decrease in forest loss at a 1% level of statistical significance.

after the program's conclusion due to conflicts with the food security objectives of certain population groups who were unable to transition to diversified agricultural systems and remained reliant on the degradation of the forest environment. To investigate this hypothesis further and gain deeper insights into regional dynamics, conducting a Benefit-Cost Analysis (CBA) using metrics such as time spent collecting firewood and the monetary value of firewood obtained/purchased would be valuable. Such an analysis could reveal whether the costs associated with resource extraction are disproportionately higher in the Central region compared to the South, where differences in forest loss trends are observed.

Furthermore, when examining the impact of the intervention across different labor options and regions, there is some indication that the intervention may lead to increased vulnerability and forest loss amongst households reliant on natural resources, particularly in the Central region (refer to Appendix B.17). The negative impact on livelihoods primarily manifests as a decrease in asset value, noticeable both two and five years after the conclusion of the policy. In terms of forest outcomes, a significant increase in forest loss is observed five years following the conclusion of the second phase of the intervention. On the other hand, results for the South region are somewhat mixed. While vulnerability persists for households dependent on agricultural labor and firewood collection, especially when considering the FCS, there appears to be no discernible effect on forest outcomes. Additionally, in this context, the intervention is linked to an uptick in non-food expenditures for households reliant on natural resources. Nevertheless, it is essential to note that these findings should be interpreted cautiously due to the limited size of the samples.

2.7 Discussion and conclusion

To date, quantitative empirical evidence suggest mixed effects with regard to the influence of forest co-management on communities' livelihoods and conser-

vation of natural resources. The objective of our analysis is to contribute to the literature with a better understanding of the behavioral channels through which co-management influences household poverty and the mechanisms by which comanagement changes behavior underlying outcomes. As a first step, we investigate the poverty and forest impacts of Malawi's Improved Forest Management for Sustainable Livelihoods Program (IFMSLP) two and five years after its conclusion. The results from our DiD framework, combined with a PSM, that we apply to our longitudinal data, suggest that the IFMSLP has increased, rather than alleviated poverty, as measured by the value of households' durable assets, non-food expenditures, and an indicator of dietary diversity and energy sufficiency, the Food Consumption Score (FCS). These effects appear to diminish overtime. Our results are generally robust to various matching combinations, samples, and model specifications, amongst other tests. Furthermore, when examining the treatment's impact on vulnerability levels based on households' portfolio of labor activities, we find that households characterized by limited labor alternatives and a dependence on resource extraction and/or agricultural production are particularly worse off.

Secondly, considering the program's conservation objectives, we examine the treatment's impact on forest loss by constructing a measure of resource scarcity based on the distance household members had to travel to collect firewood at baseline. Overall, our analysis does not reveal any significant impact of the IFMSLP on forest conditions. However, upon further investigation into regional differences, we find some evidence of a potential increase in forest loss in the Central region. We also show that the adverse effects of the treatment on household poverty outcomes are concentrated mainly in this region, where the differences in the effects, conditioned on the allocation of household labor, are also more evident compared to the South. Additionally, the observed increase in degradation in this area seems to be primarily concentrated amongst resource-dependent households. It is conceivable that if co-management practices led to a depletion of forest resources due to heightened reliance, households residing within or near the project's Impact Areas

may have experienced increased vulnerability, particularly in the absence of alternative livelihood options. An area for future research could involve determining the extent to which the observed degradation has taken place within or outside the co-management initiative. Specifically, whether it has occurred within or beyond co-managed blocks in Forest Reserves, as well as within or beyond the areas under co-management customarily claimed by communities. As emphasized in Lokina and Robinson (2008), and predicted in studies such as Lewis (2002) and Robinson et al. (2005), effective conservation of forest resources, within the framework of Participatory Forest Management (PFM), could potentially result in increased degradation of forest resources in other areas. This aligns with findings from Libois et al. (2022), which imply that the decentralization of forest management may initially restrict access to nearby forests, prompting households to collect firewood from more distant forest areas.

Overall, our results at this stage suggest that policies encouraging reliance on environmental income could potentially exacerbate poverty, particularly in the short term, if there are no alternative income-generating activities available. This finding indicates that initiatives focused on natural resource utilization might benefit from considering the diverse employment opportunities available to targeted communities, as such activities often yield low returns in the absence of other viable options. Additionally, the observed increase in poverty underscores the need to carefully weigh the costs and benefits of co-management. As highlighted earlier, while transferring access and withdrawal rights may benefit resource-utilizing households, transferring management and exclusion rights to communities could raise extraction costs. Thus, it appears important for co-management interventions to focus on establishing robust and reliable forest rights, while also enforcing clear and equitable forest management and extraction regulations. This approach could permit to enhance the market value of forest resources and help strike a balance between sustainable resource utilization and poverty alleviation objectives.

Chapter 3

Women's Empowerment, Heat Exposure, And Child Nutrition: Evidence From Sub-Saharan Africa

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This paper is a working draft.

Abstract

The association between weather anomalies, such as rising temperatures and rainfall shocks, and child malnutrition is well established. By impacting food availability, access, and utilization, climate variability contributes to several of the underlying causes of child undernutrition. In light of the pivotal role women can play in the allocation of household resources, this study explores whether higher levels of women's empowerment can help mitigate the adverse effects of high temperatures on children's nutritional well-being. We use the SWPER indicator, which permits to account for the multidimensional nature of women's empowerment, and a large panel of Sub-Saharan African countries that we follow over several years. We find that women with a higher level of empowerment, as primarily captured by an increased participation in household decisions, can be instrumental in preventing acute malnutrition in children during periods of extreme heat. This effect appears to be especially pronounced amongst children with the lowest nutritional levels. Decisions pertaining to the allocation of resources - such as food, money, time, and care - are likely to play a particularly crucial role in protecting the nutrition of the most vulnerable children in the event of a shock.

3.1 Introduction

Changes in global climate represent a severe threat to children's health and nutritional well-being. According to Rees (2021), one billion children reside in countries that are highly vulnerable to climate-related risks, and 820 million, which is more than one-third of all children worldwide, are at significant risk of heatwave exposure. Children are especially vulnerable to the impacts of high temperatures as they experience greater difficulties in self-monitoring or responding to heat stress (Zivin and Shrader, 2016), and are more frequently exposed to heat due to behavioral and social factors, which can translate into involvement in outdoor recreational activities and in agricultural tasks (Xu et al., 2012, Zivin and Shrader, 2016). Furthermore, exposure to elevated temperatures can result in a range of immediate health issues in infants and children (Baker and Anttila-Hughes, 2020). Precisely, children who are exposed to extreme heat face a heightened likelihood of contracting vector-borne and diarrheal diseases, as well as experiencing heatrelated dehydration and exhaustion (Checkley et al., 2000, Bandyopadhyay et al., 2012, Xu et al., 2013, Zhou et al., 2013, Xu et al., 2014, Carlton et al., 2016, Musengimana et al., 2016, Levy et al., 2018). As highlighted by Baker and Anttila-Hughes (2020), high temperatures' consequences for child development are likely to vary depending on the extent to which children are exposed to heat. Short-term exposure can directly impact a child's capacity to retain essential nutrients due to a loss of appetite from thermal stress, heightened dehydration, or increased instances of diarrhea, which can lead to acute malnutrition (Petri et al., 2008, Xu et al., 2014, Carlton et al., 2016, Levy et al., 2018). On the other hand, longer-term exposure may indirectly reduce nutritional intake by diminishing both agricultural yields and crops' nutritional quality (Schlenker and Roberts, 2009, Lobell et al., 2011, Field and Barros, 2014, Myers et al., 2017, Schauberger et al., 2017, Serdeczny et al., 2017, Zhao et al., 2017). Extended periods of inadequate nutrition can, in turn, result in chronic malnutrition and stunted growth, exposing children to various morbidities (Lim et al., 2012, Baker and Anttila-Hughes, 2020) and to an elevated risk of mortality (Caulfield et al., 2006, Black et al., 2008). Nutrition in the early stages of life is not only crucial for health but also holds significant economic importance due to its implications for long-term economic development (Blom et al., 2022). Indeed, nutrition plays a pivotal role in the formation of human capital through its effects on cognitive development (Blom et al., 2022). There is evidence of an association between cognitive impairment and undernutrition during the early stages of childhood (Hoddinott et al., 2013). Consequently, adverse events that occur during children's developmental stage can affect future outcomes by influencing educational attainment and adult income negatively (Blom et al., 2022).

Associations between child malnutrition and weather anomalies, such as rainfall shocks, rising temperatures, or both, have been documented in several studies, including in Hoddinott and Kinsey (2001), Grace et al. (2012), Jankowska et al. (2012), Davenport et al. (2017), Cooper et al. (2019), Baker and Anttila-Hughes (2020), Randell et al. (2020), Thiede and Strube (2020), and Blom et al. (2022). Indeed, by impacting food availability, access, utilization, and ultimately, the overall stability of the food supply, climate and weather fluctuations contribute to several of the underlying causes of child undernutrition (see UNICEF, 2016). Given the important role women can play in addressing challenges to nutrition, particularly when empowered (Santoso et al., 2019), our analysis aims to explore how women's empowerment can help mitigate the adverse effects of heatwave exposure on children's nutritional well-being. In addition to contributing to the literature on weather shocks and child malnutrition, as well as on women's empowerment and child nutrition, our study also enriches the body of research on women's role in climate change adaptation and shock mitigation.

Previous work has shed light on the important influence of maternal education in protecting child nutrition in the event of climate-related shocks. Dimitrova and Muttarak (2020) notably show that children born into economically disadvantaged households, but with educated mothers, encounter nearly identical risks of stunting as a result of a weather shock as children born into more affluent households, but to mothers who lack education. Moreover, they show that the main pathways between mother's education and improved child nutritional outcomes include better health knowledge and increased use of healthcare. Women's empowerment was found to play a more minor role. With respect to this study, our research therefore seeks to elucidate how specific aspects of empowerment contribute to improved child nutrition outcomes in the face of weather anomalies. In view of the significant role that women can play in the allocation of household resources, our central focus is on women's level of decision making, which has been linked to enhanced child nutrition (Carlson et al., 2015, Cunningham et al., 2015).

We propose a simple model of equality between partners and child nutrition that showcases how differences in preferences for child nutrition, and in bargaining power in a couple, can influence child nutrition in the event of a shock. Precisely, we show that, in a household where the mother has an increased preference for child nutrition compared to her partner, the allocation of resources to child nutrition will experience a more substantial rise following an income shock when the mother possesses greater bargaining power. We anticipate that differences in preferences between women and men are likely given evidence provided by several studies, including Eckel and Grossman (1998) and Croson and Gneezy (2009).

Within the framework of our empirical analysis, we focus on the nutritional outcomes of children under five years old using Demographic and Health Surveys (DHS) for 25 Sub-Saharan African countries across the period 2000 to 2019. We direct our attention to Africa given the continent's high vulnerability to high temperatures (Mora et al., 2017). Temperatures in the region have exhibited a consistent upward trend since the 1970s (Collins, 2011), and, according to projections, they will continue to increase (Hulme et al., 2001, Christensen et al., 2007, Pachauri et al., 2014). According to James and Washington (2013), a rise of 2 °C or 3 °C in global average temperatures may result in much larger temperature increases in certain regions of Sub-Saharan Africa, ranging from 3 °C to 5 °C. Moreover, malnu-

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trition is highly prevalent in the region - amongst the children under five who are underweight, one third resided in Sub-Saharan Africa as of 2015 (United Nations, 2015). As described earlier, in the face of hotter climate conditions, child malnutrition and the associated health challenges are expected to rise (Thiede and Strube, 2020).

In line with the literature, we find evidence of an association between heat exposure and lower weight-for-height (WHZ) amongst children under five years of age, along with an increased likelihood of being wasted. Moreover, our results suggest that women with greater levels of empowerment, as primarily captured by an increased involvement in household decisions, can effectively mitigate the negative effects of recent heat exposure on child nutrition. The tests we perform using alternative dimensions of empowerment, including intolerance to violence and autonomy, appear to corroborate that the moderating impact of women's empowerment during heat stress primarily manifests through heightened levels of decision making. Furthermore, we find that this influence is especially pronounced for children at the lower end of the distribution in terms of nutrition. Strategic decisions pertaining to the allocation of material resources, as well as the level of care provided, are likely to be especially critical in protecting the nutritional well-being of the most vulnerable children in times of shock.

The remainder of the paper is organized as follows: the next section outlines the current state of the literature to which our research contributes; Section 3.3 presents a household level model of gender inequality and child nutrition; Section 3.4 provides details on our data and variables of interest, and describes the empirical strategy; Section 3.5 presents our results, and Section 3.6 concludes.

3.2 Literature review

Our paper is at the intersection of three branches of the literature: links between weather and child nutrition, the influence of women's empowerment on child nutrition, and women's role in risk adaptation.

3.2.1 Climate variability and child nutrition

Temperature and precipitation shifts, along with the indirect consequences of these environmental changes, are anticipated to influence child nutrition by impacting the primary determinants of food and nutrition security (Thiede and Strube, 2020). These encompass food availability, access, utilization, and stability (FAO, 1996)¹. Household food insecurity can profoundly affect the growth and development of young children, especially those under five years old (Dimitrova and Muttarak, 2020). During this developmental stage, adequate nutrient intake is particularly crucial for fostering key brain processes and structures, as well as facilitating physical growth (Dimitrova and Muttarak, 2020).

Considering these aspects, risks to food availability can occur through impacts on agriculture productivity (FAO, IFAD, UNICEF, WFP and WHO, 2018). High temperatures and insufficient precipitation levels are indeed found to be associated with decreases in the yield of numerous crops, resulting in shifts in local and regional food provisions (Schlenker and Roberts, 2009, Nelson et al., 2013). As cited in Thiede and Strube (2020), impacts on crop output can stem from direct factors, such as heat stress, or indirect factors, such as from outbreaks in pests and diseases (Thornton et al., 2014). In Sub-Saharan Africa, for instance, which already records the lowest crop yields at the global level, rising temperatures were found to cause a drop in maize, sorghum, and groundnut production (Hoffman et al., 2018). In

¹Climate-related shocks can also jeopardize the basic factors of child undernutrition (refer to UNICEF, 2016) by triggering conflicts, consequently undermining household socioeconomic resources indirectly (Smith, 2014).

addition, findings suggest that climate variability could undermine the quality of the crops cultivated by small-scale farmers, with direct consequences on the nutritional content and diversity of the food available to households (Myers et al., 2014, Smith and Myers, 2018, Call et al., 2019, Headey et al., 2019, Tobin et al., 2019). Several studies, including Jones and Thornton (2003), Morton (2007), and Cohn et al. (2017), also emphasize the heightened vulnerability of households living in low-income agricultural settings to the impacts of changes in food availability. This vulnerability primarily arises from these communities' heavy reliance on-farm or local agricultural production for their food consumption (Thiede and Strube, 2020).

Changes in crop yields, agricultural production, and stocks can, in turn, cause fluctuations in food prices and purchasing power, with consequences on food access (FAO, IFAD, UNICEF, WFP and WHO, 2018, Thiede and Strube, 2020). Béné et al. (2015) provide evidence that the price of a food basket can undergo a significant increase following an adverse weather event with effects that can last for several months. Fluctuations in temperature and precipitation can also lead to income loss amongst agriculture-dependent communities, such as food producers (Hoffman et al., 2018, Thiede and Strube, 2020). As an important driver of future price trends (Nelson et al., 2010) and short-term price fluctuations, climate change, therefore, also poses a risk to the overall stability of the food system due to short-term supply variability². Additional pathways through which climate fluctuations can impede food access include impacts to off-farm employment opportunities (Mueller et al., 2020), and to household income via alterations in non-agriculture work's capacity and productivity (Dell et al., 2012, Dunne et al., 2013, Thiede and Strube, 2020).

Climate disturbances also have repercussions for food utilization by jeopardizing food's nutritional quality and safety (FAO, IFAD, UNICEF, WFP and WHO, 2018). Faced with declines in both food availability and income, coupled with

²While Wheeler and Von Braun (2013) note that climate change's impacts on the stability of the food system is more uncertain at the regional scale, the effects are likely to be more pronounced in regions that are susceptible to hunger and malnutrition.

rising prices, households may adopt coping strategies that involve decreasing the number of meals eaten per day, reducing the amount of food consumed per meal, skipping meals altogether, and opting for food of lower-nutritional value (e.g., that are not as dense in nutrients, or that are more calorie-dense) (FAO, IFAD, UNICEF, WFP and WHO, 2018). As cited in Baker and Anttila-Hughes (2020), evidence indicates that before resorting to adaptive measures like temporary migration, households will tend to reduce their food intake, especially during periods of famine (Corbett, 1988). Furthermore, changes in environmental conditions con directly influence children's capacity to effectively ingest food by contributing to a rise in morbidities such as diarrhea and vector-borne illnesses, including malaria, dengue fever and chikungunya (Kolstad and Johansson, 2011, Bandyopadhyay et al., 2012, Caminade and Jones, 2016, Mordecai et al., 2020). Checkley et al. (2000) specifically show that for every 1 °C temperature increase, the rate of children hospitalized due to diarrhea increases by 8%. Impacts to adult health due to weather variability can also compromise the well-being of children by reducing the amount of care and resources devoted to them (Lohmann and Lechtenfeld, 2015, Mueller and Gray, 2018, Pailler and Tsaneva, 2018). Crop and food contamination, as well as the proliferation of pests and diseases induced by climate variability, also pose a risk to food safety and prevent the consumption of foods rich in micronutrients (FAO, IFAD, UNICEF, WFP and WHO, 2018).

As highlighted by Thiede and Strube (2020), given the evidence on the direction of the impact of temperature and precipitation variations on crop yields, farm income, and the prevalence of diseases, it can be expected that hotter and more arid climatic conditions are likely to contribute to malnutrition in children. Associations between malnutrition and reductions in precipitation levels, rising temperatures, or both, have been documented in several studies, including Hoddinott and Kinsey (2001), Grace et al. (2012), Jankowska et al. (2012), Davenport et al. (2017), Cooper et al. (2019), Randell et al. (2020), Thiede and Strube (2020), and Blom et al. (2022). It is also worth noting that the impact of climate shocks on a child is contingent upon the household's capability to effectively respond to such adverse events (Dimitrova and Muttarak, 2020). As highlighted in Dimitrova and Muttarak (2020), more affluent households typically exhibit stronger resilience during climatic shocks, as they can tap into their savings or access better credit options. By being able to maintain stable consumption patterns, these households possess greater means to protect children from undernutrition (Dimitrova and Muttarak, 2020).

In this work, we specifically direct our attention to children's heat exposure given that one third of children globally experience high ambient temperatures (Rees, 2021), with direct and indirect implications on their short- and long-term health and nutritional well-being. Children are particularly vulnerable to elevated temperatures as they lack the ability to self-monitor or respond to heat stress (Zivin and Shrader, 2016). They are also frequently subjected to heightened heat exposure due to behavioral and social factors, such as outdoor play or involvement in agricultural tasks (Xu et al., 2012, Zivin and Shrader, 2016). Moreover, the consequences for child development are expected to differ depending on the degree of exposure to heating (Baker and Anttila-Hughes, 2020). High temperatures that span for days to weeks can hinder a child's development by directly impacting their capacity to retain essential nutrients (Baker and Anttila-Hughes, 2020). This occurs through factors such as appetite loss induced by thermal stress, heightened dehydration, or increased instances of diarrhea, which can lead to inadequate absorption of nutrients and calories, and ultimately result in weight loss (Petri et al., 2008, Xu et al., 2014, Carlton et al., 2016, Levy et al., 2018). Over extended periods, elevated temperatures may indirectly reduce nutritional intake by diminishing both overall agricultural yields and the nutritional quality of the harvest (Schlenker and Roberts, 2009, Lobell et al., 2011, Field and Barros, 2014, Myers et al., 2017, Schauberger et al., 2017, Serdeczny et al., 2017, Zhao et al., 2017).

3.2.2 Women's empowerment and child nutrition

The conceptual framework developed by UNICEF in 1990 outlines several underlying factors that contribute to child undernutrition, including household food insecurity, insufficient care and feeding practices, as well as an unhealthy household environment and a restricted access to healthcare (UNICEF, 2016). While climatic conditions were not initially considered within the UNICEF framework in the early 1990s, it later became evident that extreme climate events and variability are significant disruptors of resources and livelihoods (Dimitrova and Muttarak, 2020), and are, hence, capable of exacerbating several underlying causes of undernutrition, as highlighted in Section 3.2.1. With these considerations in mind, Santoso et al. (2019) draw from this framework to shed light on the several channels through which empowered women can help address nutritional challenges in children. Investigating whether heightened levels of women's empowerment can alleviate some of the detrimental impacts of climate change on child nutrition is therefore particularly compelling.

However, before we delve into the pathways linking women's empowerment and child nutrition, it's essential to first clarify the concept of empowerment, an intricate term subject to multiple definitions. The World Bank defines empowerment as "the process of enhancing an individual's or group's capacity to make purposive choices and to transform those choices into desired actions and outcomes" (Alsop et al., 2006). For Duflo (2012), the empowerment of women, more precisely, involves the enhancement of their ability to access key elements of development, including health, education, income-generating opportunities, rights and political engagement. On the other hand, Kabeer (2005) proposes to explore the concept of women's empowerment via three areas: agency, resources, and achievements. This approach is helpful for classifying and organizing measures related to empowerment and addressing its multifaceted aspects. Agency is defined by the author as the process by which decisions are formulated and implemented. Measures of empowerment that could fall under this domain include indicators that assess a women's ability to make different kinds of decisions (Santoso et al., 2019). As for resources, they are characterized by Kabeer (2005) as the means by which agency is expressed, while achievements denote the outcomes of that agency. Indicators that could fall under the resources category include "women's education, social capital, and asset ownership" (Santoso et al., 2019). As for achievements, the latter could encompass increased labor market participation, domestic violence intolerance, and more time dedicated to child care (Santoso et al., 2019).

This being said, one of the first dimensions of women's empowerment that could lead to improved child nutrition, according to Santoso et al. (2019), involves women's ability to access resources. This domain precisely encompasses "a woman's mobility, access to information, or agency over agricultural decisions". Greater mobility can indeed lead to improved access to various household resources, with potential benefits for child nutrition. Benefits to child nutrition can also result from women's increased participation in agriculture-related decisions, which can be associated with greater technical efficiency in farming, and, hence, contribute to improved food security at the household level (Sharaunga et al., 2016, Santoso et al., 2019, Tsiboe et al., 2018).

The second area of women's empowerment highlighted by Santoso et al. (2019) pertains to the share of household resources allocated to child nutrition, which the authors divide into the following sub-groups: 1) allocation of material resources, such as money and food; 2) allocation of women's time and that of household members; 3) decisions pertaining to the care and health of children; and 4) decisions pertaining to women's own health and nutrition. When it comes to material resource allocation, there is evidence that the more women are involved in decision making at the household level, the more resources are dedicated to the nutrition and health of children. For instance, money managed by women is more inclined to be utilized for buying food (Quisumbing and Maluccio, 2003, Porter, 2016) and healthcare (Babu et al., 1993, UNICEF, 2011). With respect to women's time, an

uneven allocation of household chores, or increased women's time spent on agriculture labor can, for instance, result in them compromising the time dedicated to childcare, with consequences on child nutrition (Engle et al., 1999, Blackden and Wodon, 2006, Johnston et al., 2018). Finally, the decisions relative to childcare and paternal care are also key determinants of child nutrition. In the first case, it has been proven that empowered women, through their decisions regarding the allocation of material resources and time, are better situated to oversee and address their children's health needs (Santoso et al., 2019). With respect to parental care, women's autonomy in choosing activities and accessing resources that are beneficial to their health and nutrition is also vital in this regard. For example, as underlined by Nnam (2015) and Wrottesley et al. (2016), and as also cited in Santoso et al. (2019), mothers' nutritional well-being throughout their lives plays a crucial role in ensuring the health of newborns and in reducing the risks of fetal and infant mortality, underdevelopment, low birth weight, early birth, and impaired brain development, amongst other health issues. Following childbirth, mother's physical health remains essential in maintaining their ability to provide their child with sufficient food and care (Engle et al., 1999).

The last pathway outlined in Santoso et al. (2019)'s framework relates to women's reproductive decisions. Indeed, empowered women have a higher chance of being able to utilize modern contraception, while having access to antenatal care and skilled childbirth assistance (Tadesse et al., 2013, Msuya et al., 2014, Pratley, 2016), in turn, limiting the risk of complicated pregnancies that could lead to unfavorable birth outcomes (Conde-Agudelo, 2000, Paranjothy et al., 2009, Hoque, 2012, Goisis et al., 2017).

3.2.3 The role of women in protecting child health

In view of the evidence suggesting that adverse weather events can contribute to child malnutrition, and the diverse pathways linking women's empowerment to improved child nutritional well-being, this study aims to investigate how women with higher levels of empowerment may play a role in mitigating the detrimental effects of heat stress on child nutrition.

Amongst the prior research that examine the role of women in protecting the health of their children in times of crises, one noteworthy study is by Dimitrova and Muttarak (2020). This work investigates the protective role of women's education in particular, recognizing its crucial impact on promoting child health, nutritional well-being, and ultimately, survival (Fuchs et al., 2010, Arthur et al., 2015, Alderman and Headey, 2017). Specifically, Dimitrova and Muttarak (2020) explore how mother's education serves as a protective factor for child nutrition compared to household wealth, and examines the mechanisms by which maternal education influences child nutrition. Their results suggest that mother's education plays an important role in moderating the effects of weather anomalies on child health. They show that children born into economically disadvantaged households, but with educated mothers, encounter nearly identical risks of stunting as a result of a weather shock as children born into more affluent households, but to mothers who lack education. Additionally, their findings reveal that the main pathways through which mother's education leads to improved health outcomes for her children include enhanced health knowledge and increased utilization of healthcare. On the other hand, despite evidence of associations between women's education and increased decision making, health care spending, and mobility (Bloom et al., 2001, Becker et al., 2006), Dimitrova and Muttarak (2020) find a lesser influence of female empowerment when it comes to the links between mother's education and child nutrition.

With respect to this work, our research seeks to elucidate how specific aspects of empowerment contribute to improved child nutrition outcomes in the face of weather anomalies, while controlling for education³. In light of the important role

³A student paper by Villanueva (2022) has explored whether women's empowerment could protect child nutrition in the face of a weather shock using one wave of DHS data for Mozambique. Results suggest that exposure to droughts or floods during pregnancy is positively correlated with

women can play in the allocation of household resources, we primarily focus on mother's level of decision making, which was also found to be associated with improved child nutrition (Carlson et al., 2015, Cunningham et al., 2015). As cited in Dimitrova and Muttarak (2020), this is especially pertinent in lower-income settings, where the likelihood for women to allocate resources towards the well-being of children is greater than that of men (McKenna et al., 2019). We therefore expect that during climate-related shocks, women with greater decision power will be inclined to allocate more resources to child nutrition. To support this rational, we introduce in Section 3.3 a simple model of inequality between partners and child nutrition at the household level. Notably, we show that in a household where the mother has an increased preference for child nutrition compared to her partner, the allocation of resources to child nutrition will experience a more substantial rise following a shock when the mother possesses greater bargaining power. We anticipate that differences in preferences between women and men are likely given evidence provided by several studies, including (Eckel and Grossman, 1998) and (Croson and Gneezy, 2009).

Empirically, we investigate the potential contribution of women's empowerment to child nutrition in the event of heat exposure across several countries and across time, allowing to account for both spatial and temporal variations. We do so while using the SWPER indicator, which integrates three central dimensions of women's empowerment: women's attitude to violence, autonomy, and decision making. Although we mainly focus on decision making, we also investigate the moderating influence of the two other domains of empowerment. Secondly, we contribute to the literature by examining how effects might vary according to different child nutrition levels. The child's initial nutritional condition is likely to offer some insights into the overall vulnerability of the household in which she was born, and hence, on the latter's adaptive capacity. The likelihood for a child to suffer from acute malnutrition after being exposed to heat is therefore expected to differ according to

child stunting. Nonetheless, the study does not find any evidence indicating a connection between women's empowerment and weather shock mitigation.

where the child stands in the distribution in terms of nutrition. As a consequence, the influence of women's decision making could also vary.

3.3 A simple model of gender inequality and child nutrition within the household

3.3.1 Set up

A household considers the share δ of resources R to be allocated to child nutrition. Decisions in the household are taken through Nash bargaining between two members, with heterogeneous preferences. As a matter of simplicity, the two members are called F (she) and M (he).

The *F* and *M* net utility from child nutrition are respectively $U_F(\delta)$ and $U_M(\delta)$. We assume by convention that *F* has stronger preferences for child nutrition: $U_F(\delta) > U_M(\delta)$, $\forall \delta \in [0, 1]$. As functional forms, we can use:

$$\begin{split} U_F(\delta) &= a_F \delta R - \frac{1}{2} (\delta R)^2 \\ U_M(\delta) &= a_M \delta R - \frac{1}{2} (\delta R)^2 \end{split} \tag{3.1}$$

Net utility from child nutrition combines the utility derived from improving the well-being of children within the household, and the opportunity cost of those expenses. As a matter of simplicity, we write: $a_M = \beta a_F$, with $\beta \in [0, 1]$, suggesting that *F* has higher a preference for child nutrition than *M*. First-order conditions implicitly give the preferred child nutrition share: $\delta_F^*(a_F, R) > \delta_M^*(a_F, \beta, R)$.

Using our functional forms, we get: $\delta_F^*(a_F, R) = \frac{a_F}{R} > \delta_M^*(a_F, \beta, R) = \frac{\beta a_F}{R}$, for $\beta < 1$. Those shares are decreasing in income: $\frac{\partial \delta_F^*}{\partial R} = \frac{-a_F}{R^2} < 0$, $\frac{\partial \delta_M^*}{\partial R} = \frac{-\beta a_F}{R^2} < 0$, with income elasticities: $e_F = \frac{-a_F^2}{R^2}$ and $e_M = \frac{-(\beta a_F)^2}{R^2}$. The child nutrition elasticity to income is smaller for the household member (here *M*) who has the smallest
preference for child nutrition (as $\beta < 1$).

3.3.2 Nash bargaining

Let's consider that *F* and *M* make their choices regarding resource allocation to child nutrition through a Nash bargaining process, where *F* and *M* have bargaining powers denoted by α and $(1-\alpha)$, respectively. The Nash bargaining takes the form:

$$\max_{\delta} U_F(\delta)^{\alpha} U_M(\delta)^{1-\alpha}$$
(3.2)

The first-order condition implicitly gives the share of resources allocated to child nutrition $\delta^*(\alpha, \beta, R)$:⁴

$$\alpha \frac{U'_F(\delta^*)}{U_F(\delta^*)} = -(1-\alpha) \frac{U'_M(\delta^*)}{U_M(\delta^*)}$$
(3.4)

By construction, we have $\delta^* \in [\delta^*_M; \delta^*_F]$, and we get closer to δ^*_F as bargaining power α increases. Several insights can be derived from equation (1):

- Preference for child nutrition: the share of resources allocated to child nutrition increases with *M*'s preference for child nutrition: ∂δ^{*}/∂β > 0. If *F* and *M* have similar preferences over child nutrition, *F*'s bargaining power has no impact on the share of resources allocated to child nutrition: δ^{*} = δ^{*}_M = δ^{*}_F, ∀β = 1.
- Bargaining power: whenever M has smaller preferences over child nutrition (β < 1), the chosen share of resources allocated to child nutrition is increasing in F's bargaining power: ∂δ*/∂α > 0, ∀β < 1. If F and M have similar preferences, F's bargaining power has no influence on this share: ∂δ*/∂α = 0, ∀β = 1.

⁴Using the functional form for U_F and U_M brings:

$$\alpha (a_F - R\delta^*) (\beta a_F - \frac{R}{2}\delta^*) + (1 - \alpha)(\beta a_F - R\delta^*) (a_F - \frac{R}{2}\delta^*) = 0 \tag{3.3}$$

 Income: the share of resources allocated to child nutrition is decreasing in income: ^{∂δ*}/_{∂R} = −^{δ*}/_R < 0



preference for child nutrition β

(b) δ^* increases with *F*'s bargaining power α

(c) δ^* decreases with the household's resources *R*

Figure 3.1: Factors influencing the allocation of resources to child nutrition δ^*

3.3.3 Income shock and bargaining power

The impact of a negative income shock on the share of resources allocated to child nutrition depends on M's preference for child nutrition β and F's bargaining power. First, we take the case of similar preferences within the household. In this situation, the impact of the income shock on share δ^* will not depend on F's bargaining power: $\frac{\partial^2 \delta^*}{\partial R \partial \alpha} = 0$, $\forall \beta = 1$. Second, if F and M have different preferences, F's bargaining power has an influence. It was shown in the previous section that the income elasticity of δ^* to R is larger for F than for M; it follows that when income decreases, the rise in δ_F^* is larger than the increase in δ_M^* . Since a larger bargaining power gives more weight to F's preferences, we can conclude that, when a negative income shock occurs, the increase in the share of resources allocated to child nutrition is larger when F has more bargaining power: $\frac{\partial^2 \delta^*}{\partial R \partial \alpha} > 0$, $\forall \beta < 1$.



Figure 3.2: Income shock and bargaining power

3.4 Data and methodology

3.4.1 Data

Information on dimensions of women's empowerment, child anthropometry, individual and household characteristics, as well as contextual variables including precipitation and temperature, is derived from the Integrated Public Use Microdata Series database (IPUMS-DHS). IPUMS-DHS harmonizes Demographic and Health Surveys (DHS), which are widely used nationally-representative surveys on population, health, and nutrition, and hence, facilitates analyses across countries and across time. Precisely, the final dataset combines a series of DHS surveys from 25 African countries⁵, over the period 2000-2019 (see Appendix C.1 for the list of countries, with their respective survey years). All of the surveys are derived from the children record, whereby children under the age of five serve as the unit of analysis. Nonetheless, the children record also contains variables that pertain to mothers and households. Specifically, the data collected is obtained by interviewing women of reproductive age (15 to 49 years old) who are asked to provide information about themselves, as well as about their children and other household

⁵Our final set of results is however based on 21 countries, due to missing information in Liberia, Togo, Niger and Lesotho.

members.

3.4.1.1 Child nutrition

The indicators of child nutrition used in this analysis are the weight-for-height z-score (WHZ) and wasting, which is characterized by a WHZ that is more than two standard deviations below the reference WHZ median value⁶. These anthropometric measures were computed using the World Heath Organization (WHO) Child Growth Standards (World Health Organization, 2006), and permit to determine whether a child suffers from acute malnutrition. Together with stunting, underweight and micronutrient deficiencies, low weight-for-height (or wasting) comprises one of the four sub-forms of undernutrition (World Health Organization, 2021). Low weight-for-height is typically representative of a recent and significant weight loss due to insufficient food intake and/or as a result of an infectious disease, such as diarrhea (World Health Organization, 2021). Wasted children are more prone to chronic undernutrition (Richard et al., 2012, Schoenbuchner et al., 2019), have a weaker immune system (Rytter et al., 2014), which increases their susceptibility to other morbidities (Chang et al., 2013), and are at heightened risk of mortality (McDonald et al., 2013). Additionally, there is evidence that wasting is associated with impaired cognitive development in later stages of life (Khandelwal et al., 2020). As underlined by Thiede and Strube (2020), the prevalence of wasting therefore carries implications for human development both in the short and long term.

3.4.1.2 The SWPER

To capture the level of women's empowerment, this study mobilizes the Surveybased Women's emPowERment index (SWPER) for the African region, developed by Ewerling et al. (2017). The SWPER allows to account for the multidimensional

⁶A child who has a WHZ that falls more than three standard deviations below the median of international standards is considered as severely wasted (De Onis et al., 1997).

and multilevel nature of women's empowerment, while enabling cross-country comparisons and time trend analyses. The SWPER proposed for African countries was constructed using DHS surveys from 34 countries in Africa, from which 15 questions pertinent to empowerment, and common to all surveys, were mobilized (Ewerling et al., 2017) (see Appendix C.2 for specific items). In order to render the SWPER applicable to all countries in the region, the authors performed a principal component analysis on the combined dataset, from which three broad dimensions of women's empowerment were derived, including women's attitude towards violence, involvement in household decisions, and social independence. With respect to the dimension that concerns women's attitude to violence, it consists of questions linked to whether female respondents consider wife-beating to be justified or not in different situations. As for social independence, it mainly encompasses items that pertain to education, access to information through newspapers or magazines, as well as the age at which the woman gave birth to her first child, and the age at which she cohabited with a partner for the first time. Finally, the decision making domain comprises questions related to the woman's level of involvement in household level decisions, on matters such as health care, large purchases and visits to family or relatives, as well as on whether she has worked in the past 12 months (to a lesser extent, nonetheless).

In summary, and as highlighted in Ewerling et al. (2020), the social independence domain primarily comprises preconditions that empower women to attain their objectives. The attitude to violence dimension, on the other hand, is closely linked to the concept of intrinsic agency, also known as power within, which refers to, as formulated in Ewerling et al. (2020), as the "process by which one develops a critical consciousness of one's own aspirations, capabilities, and rights" (Batliwala, 1994, Kabeer, 1999, Miedema et al., 2018). It can be regarded as both an asset and an opportunity in ensuring environmental safety, or alternatively, as a proxy for agency, as a safe environment facilitates a greater capacity to exercise choice (Miedema et al., 2018). Finally, the SWPER's decision making score can serve as an indicator of instrumental agency, which can be defined as a women's capacity to make choices at the household level (Miedema et al., 2018). We therefore assume that women with a higher decision making score are likely to exert influence across various household matters, such as resource allocation, childcare, agricultural decisions, and labor allocation.

Moreover, because some questions relevant to empowerment were only asked to women who are currently married or in a union, the SWPER is constructed for this category of women only. Furthermore, within the framework of their analysis, Ewerling et al. (2017) imputed data points pertaining to women with no children using single hot-desk imputation, while creating clusters of women based on age of first cohabitation. This was justified by the fact that between 5% and 10% of women reported to be childless when the questionnaire was administered. In this analysis, we follow these exact steps to construct the SWPER, as detailed by the authors.

The score associated to each domain are standardized such that a zero value indicates that the country has a score that is equal to the average in Africa. As a result, positive values suggest that the situation in the country is better than the average while negative values imply a worse situation with respect to the average (Ewerling et al., 2017). The index can be computed for any country in Africa. Moreover, the authors find a high correlation between the SWPER and the Gender Development Index (GDI), a widely recognized country-level measure of "gender gaps in human development achievements in health, education, and income" (Qadir, 2015, Ewerling et al., 2017). With regard to the GDI, one of added values of the SWPER is that it can also be applied at the individual level.

3.4.1.3 Heat exposure

By making use of the georeferenced information available in DHS's GPS datasets, IPUMS-DHS offers a range of contextual variables related to the "physical environ-

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ment, economic and population features, and agriculture" (Boyle et al., 2020). These variables are associated to individual and household records and are computed around DHS cluster locations (Boyle et al., 2020). Amongst these contextual variables are environmental factors such as precipitation and temperature, which are of particular interest to this analysis. Regarding temperature, IPUMS-DHS reports both average minimum and maximum temperatures over a specified period, initially expressed in Kernal degrees. However, we convert these values to degrees Celsius. The temperature data is available for a period of 72-months within a 10km radius of DHS cluster location points (Boyle et al., 2020). Originally sourced from the Terrestrial Hydrology Research Group at Princeton University (Sheffield et al., 2006), this dataset spans 50 years, from January 1980 to September 2018. In our primary analysis specification, we focus on children's heat exposure in the three months preceding the survey. Given our study's emphasis on acute malnutrition, accounting for recent heat exposure is crucial. As noted in Blom et al. (2022), a three-month time-frame is sufficiently long for potential fluctuations in weight to occur and is short enough to presume that children are unlikely to have recovered from a serious disturbance. Therefore, our main "temperature shock" measure identifies whether children under five have experienced monthly average maximum temperatures exceeding 30 °C in the three consecutive months preceding the survey.

Furthermore, we also mobilize information on precipitation levels within the framework of our control variables. Similarly, the precipitation measure (expressed in milliliters) is reported each month for up to 60 months prior to the survey, and up to 11 months after the survey. It is also available within a 10-km circular buffer around each DHS cluster (Boyle et al., 2020).

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3.4.1.4 Descriptive statistics

Figure 3.3 illustrates the correlation between the average WHZ of children under five and the mean score of the SWPER decision making domain at the country level. There appears to be a positive correlation between both measures - when women's decision making increases, there is a tendency for child's WHZ to increase as well. Nonetheless, the data points show some spread, indicating variability across observations. Burkina Faso, Niger, Chad, Ethiopia, Senegal and Mali, which exhibit amongst the lowest WHZ values, also rank amongst the countries with the lowest scores in terms of women's decision power. In our sample, the prevalence of wasted children in these countries respectively stands at 19%, 16%, 15%, 12%, 9%, and 13%. Conversely, Rwanda, which has the highest mean WHZ value, and, hence, a substantially lower proportion of children suffering from wasting, at only 3%, is amongst the countries that are the better off in terms of decision making. Although a similar trend can be observed in several other countries, both indicators do not consistently align in the same direction. A notable example is Madagascar, which, despite having one of the lowest mean WHZ values, also showcases one of the highest average decision making scores. The figures in Appendix C.4 further highlight the differences in outcomes related to child nutrition and women's empowerment between countries by ranking them according their respective scores. As also noticeable in the scatter plot, we can namely observe in these figures that close to half of the countries in our sample have a mean decision score that is below the African average (which is indicated by a decision making score below 0). Moreover, it is important to note that due to missing information with respect to average monthly temperature in Liberia, Togo, and Niger, and the absence of data on mother's height in Lesotho, the estimation results in subsections 3.5.1 and 3.5.2 do not include these countries. The final set of results is therefore based on the remaining 21 countries.



Figure 3.3: Mean WHZ and mean decision making score by country

3.4.2 Empirical strategy

To examine the influence of heat exposure on child nutrition and assess the role of women's empowerment as a potential mitigating factor, we first employ a linear regression with high-dimensional fixed effects, as detailed in Equation 3.5 of Section 3.4.2.1. Next, to broaden our understanding of disparities in child health, shock resilience, and in potential adaptation strategies, critical for targeted intervention design, we explore in Section 3.4.2.2 how the effects of heatwave exposure and the moderating influence of women's empowerment vary across different levels of child nutrition. This involves modeling an unconditional quantile regression (UQR) utilizing recentered influence functions (RIFs), a method pioneered by Firpo et al. (2009).

3.4.2.1 Linear model with high dimensional fixed effects

As mentioned, we begin by estimating a linear model with high dimensional fixed effects using Correia (2017)'s estimator. Our outcomes are comprised of the z-

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score for weight-for-height (WHZ) and of a binary variable that determines whether the child suffers from wasting or not. Closely following Blom et al. (2022)'s specification, we model the nutritional status, denoted as N, of child $_i$ in cluster $_v$ of month $_m$ and year $_y$ as follows:

$$N_{ivmy} = \beta_0 + \beta_1 Heat_{vmy} + \beta_2 Emp_{iv} + \beta_3 Heat_{vmy} * Emp_{iv} + \beta_4 X_{ivmy} + \phi_{rm} + \mu_{ry} + \epsilon_{ivmy}$$

$$(3.5)$$

 N_{ivmv} refers to the measures of acute malnutrition for children aged 0-59 months, namely the WHZ and the binary wasting variable (where 1 indicates that the child is wasted). Heat $_{vmy}$ is a dichotomous variable that equals '1' if the maximum average temperature per month exceeded 30 °C in the three consecutive months preceding the survey date, and '0' otherwise. However, we also explore different durations of heat exposure, ranging from 4 to 6 months in the Appendix. We look at the effect of temperatures above 30 °C following Blom et al. (2022)'s findings showing that children recently exposed to temperatures between 30 and 35 °C experienced a decrease in their WHZ. Furthermore, the level of women's empowerment is denoted by Emp_{in} and is captured by the SWPER indicator. In our primary models, we specifically use the SWPER score that reflects women's involvement in household decisions, aligning with our conceptual framework outlined in Section 3.4. While we employ the continuous form of the decision making score in our main specifications, we also conduct estimates using the indicator categorized into tertiles to distinguish between lower, intermediate, and higher levels of empowerment in Appendix C.5. Additionally, we conduct tests using the other dimensions of the SW-PER - attitude to violence and social independence, respectively. As a robustness check, we also utilize an alternative indicator of women's decision power.

The interaction between $Heat_{vmy}$ and Emp_{iv} seeks to assess the degree to which increased levels of women's empowerment contribute to alleviating the potential adverse effects of heat on child nutrition. A positive coefficient, that is statistically significant, would provide evidence of a protective role of women's empowerment

for child nutrition in the event of a shock. Subsequently, X_{ivmu} encompasses our child, mother, and household level explanatory variables, as well as weather-related controls. At the child level, we control for age (in months), sex, and birth order (count), while at the mother level, we account for age (in years), height (in centimeters), and the number of years of education. Furthermore, at the household level, we control for the number of children under five who live under the same roof, the sex of the household head, the source of drinking water (piped, well, and other), the type of sanitation (flush, pit latrine, and other), wealth, as captured by a wealth index (in quintiles), as well as residence location (urban or rural). We include similar controls as in Blom et al. (2022), and as in Dimitrova and Muttarak (2020), which are well documented determinants of children's nutritional well-being (see Behrman and Skoufias, 2004, Black et al., 2013, Smith and Haddad, 1999, Yisak et al., 2015). With respect to weather, we include a measure that categorizes average precipitation according to the following levels: <100mm, 100–200 mm, 200–300 mm, or >300 mm. In the same way as our heat exposure variable, the precipitation measure accounts for the average precipitation levels three months prior to the date of the interview. As described in Section 3.2.1, precipitation anomalies can also be associated to child malnutrition.

Lastly, we incorporate regional fixed effects by separately interacting region fixed effects with interview month $_r$ and with interview year $_y$, as represented by ϕ_{rm} and μ_{ry} respectively. As described by Blom et al. (2022), these regional fixed effects permit "to control for local seasonality and local year-to-year trends in child nutrition". This gives rise to some temporal and spatial variations. Indeed, variations overtime arise when we compare children who reside in the same region and who are interviewed in the same month but not in the same year. Regarding spatial disparities, these occur when we compare children who share both the same month and year of the interview, but who live in distinct climatic zones within the same geographical area (here, the region) (Blom et al., 2022)⁷. It is worth noting

⁷As also underlined by Blom et al. (2022), including fixed effects at the DHS cluster, which represents a lower geographical scale than the region, would remove both the variation across time

that, as we do not have panel data, our estimations solely capture between-group variation rather than within-group variation. Consequently, we do not control for unobserved individual characteristics that remain constant over time.

3.4.2.2 Investigating distributional effects using Recentered Influence Function Regressions (RIF)

Influence Functions (IFs) and Recentered Influence Function Regressions (RIFs) are methods that have emerged as means to examine statistics' robustness to outliers and to make statistical inferences from intricate statistics (Hampel, 1974, Efron, 1982, Deville, 1999, Cowell and Flachaire, 2015). The use of RIF regressions, specifically, have notably been popularized by Firpo et al. (2009), who use this strategy to estimate unconditional quantile regressions (UQRs).

One of the primary advantages of UQRs, in comparison to conditional quantile regressions (CQRs), is that the unconditional quantiles do not depend on the values of the independent variables in the model. As a result, paraphrasing Park (2015), the approach allows to better account for the impacts of specific parameters on the response variable, which are not captured by the conditional effects. While both conditional and unconditional quantile regressions allow the covariates to have varying effects across the distribution of the independent variable, the UQR estimates the change in Y at the τ th quantile whereas the CQR assesses the conditional change in Y at the τ th quantile. Unlike the UQR, the CQR therefore measures the effect of an explanatory variable on a quantile, conditional on specific values of the other covariates in the model (Park, 2015).

This being said, the IF, which evaluates the effect of a specific observation on a distributional statistic $v(F_Y)$, can be defined as follows:

$$IF(y_i, v(F_Y)) = \lim_{\epsilon \to 0} \frac{v((1-\epsilon)F_Y + \epsilon H_{yi}) - v(F_Y)}{\epsilon}$$
(3.6)

and across space, as the clusters are not repeatedly sampled.

where y_i is the outcome of interest of the *i*th individual, F_Y is the cumulative distribution function (c.d.f) of Y, H_{yi} is a distribution that puts mass at the value y_i , and where $v(F_Y)$ is the functional form utilized to estimate a statistical measure related to the distribution of Y, such as the median, the interquantile range, quantiles, Theil, Gini etc. As we are specifically interested in quantiles, we can define the τ th quantile of Y as:

$$IF(y_i, (F_Y)) = \left[\frac{\tau - I[Y \le q_\tau]}{f_y(q_\tau)}\right]$$
(3.7)

where, as described in Park (2015), q_{τ} is the τ th quantile of the unconditional distribution of *Y*, and $f_y(q_{\tau})$ represents the probability density function of *Y*, which is assessed at q_{τ} . As for $I[Y \leq q_{\tau}]$, it designates whether the value observed is less than or equal to q_{τ} . As noted by Rios-Avila (2020), instead of directly using the IF, Firpo et al. (2009) suggest employing the RIF, which is the recentered form of the distributional statistic of interest. We obtain the RIF by adding the corresponding statistics, in our case quantiles, to the IF:

$$RIF(y_i, q_\tau) = q_\tau + IF(y_i, q_\tau) \tag{3.8}$$

This expression represents the relative influence that observation y_i has on the computation of q_{τ} (Rios-Avila, 2020). It can also be viewed as an estimate of q_{τ} that takes into account the influence of observation y_i (Rios-Avila, 2020). The most straightforward way to estimate an UQR using RIF, following Firpo et al. (2009), is to assume that there exists a linear relationship between $RIF(y_i, q_{\tau})$ and the explanatory variables X. Given this assumption, one can employ an Ordinary Least Squares to estimate a linear model that depicts the influence of small variations in the distribution of the covariates on the τ th quantile (Rios-Avila, 2020). The RIF of the τ th quantile of Y is expressed as Equation 3.8, and the sample estimate of the unconditonal τ th quantile is used to estimate $q\tau$ (Park, 2015). As for the probability

density function $f_y(q_\tau)$, it can be approximated non-parametically using a kernel density function (Park, 2015). In contrast to a standard linear regression, RIF-OLS utilizes the $RIF(y_i, q_\tau)$ for each observation y_i in the dataset as the outcome, and this value is regressed on the observed independent variables (Rios-Avila, 2020). The linear RIF regression for child nutrition is given as:

$$RIF(N_{ivmy}, q_{\tau}) = \beta_0 + \beta_1 Heat_{vmy} + \beta_2 Emp_{iv} + \beta_3 Heat_{vmy} * Emp_{iv} + \beta_4 X_{ivmy} + \phi_{rm} + \mu_{ry} + \epsilon_{ivmy}, \quad E(\epsilon_i) = 0$$

$$(3.9)$$

To harmonize the notation between Equation 3.5 and Equation 3.9, we write $RIF(N_{ivmy}, q_{\tau})$, which is the RIF transformation of the nutritional status N (in this case of the WHZ) of child i, in cluster v, of month m and year y. To investigate how heat exposure, and the moderating impact of women's empowerment, may vary according to different levels of child nutrition, we transform our outcome variable WHZ using the RIF for different quantiles; notably quantiles 10, 50 and 90 (we show results for quantiles 25 and 75 in the Appendix). We include the same independent variables and fixed effects as in Equation 3.5, and, as previously, we look at the mitigating effect of women's empowerment using the continuous SWPER's decision making score. Results from RIF regressions are estimates of the unconditional quantile marginal effects (Park, 2015). Via Equation 3.9, we estimate the marginal effect on child nutrition at the τ th quantile related to a minor change in a specific covariate. As opposed to conditional effects, it is considered that unconditional quantile effects are more precisely estimated (Frölich and Melly, 2013). Additionally, quantile effects offer robustness to outliers (Park, 2015).

Given that our independent variable of interest, the binary temperature measure, operates at the level of the DHS cluster, we adjust our standard errors at this level to mitigate within-cluster correlation. Furthermore, when RIFs for unconditional quantiles are estimated, Firpo et al. (2009) recommend bootstrapping standard errors or at the minimum requesting robust standard errors (Rios-Avila,

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2020). As explained by Rios-Avila (2020), this is due to the fact that the computation of RIFs for unconditional quantiles entails estimating density functions, which are treated as known parameters when asymptotic errors are calculated. Standard errors are robust in all of our estimations, and we present results with bootstrapped standard errors in the Appendix.

3.5 Results

3.5.1 Main Results

The results in Table 3.1 indicate that exposure to temperatures that exceed an average of 30 °C for three consecutive months reduces the WHZ and increases the probability of child wasting. Indeed, we observe that average temperatures exceeding 30 °C decrease the WHZ by 0.12 standard deviations at a 1% level of significance (column 1), and increases the probability of wasting by 0.6 percentage points at a 5% level of significance (column 2). When we turn to the interaction between the temperature variable and the indicator of women's empowerment, we can note that it plays a role when we consider the probability of wasting as the main outcome. The direction of the effect suggests that, in times of heat, women with higher levels of decision making contribute to reducing the likelihood of child undernutrition.

For robustness, we conduct several additional tests. First, we run the same estimations as in Table 3.1 while using the decision making indicator categorized into tertiles, with the first tertile representing the lowest decision making values, the second tertile representing intermediate values, and the third tertile comprising the highest decision making scores. The objective is to differentiate between different levels of empowerment. It is worth noting, however, that within the framework of the SWPER Global, Ewerling et al. (2020) propose specific cut-off points for each dimension of the measure to differentiate between low, medium, and high empowerment. The results in Appendix C.5 show that women in the higher tertiles of decision making contribute to alleviating the negative effects of high temperatures on both the WHZ and wasting measures, compared to women in the lowest tertile.

Secondly, we utilize an alternative indicator of decision power, which captures whether women participate in decisions linked to their health care, large household purchases, and visits to family or relatives (see Appendix C.6). Precisely, the measure takes '1' if women have taken at least one of these respective decisions alone or jointly with their husband/partner, and '0' if they have no say in the making of any of these decisions. In a similar way as with the SWPER decision making score, we posit that involvement of women in these decisions implies their influence in other decision making realms, including those related to child care. In line with the results in Table 3.1, we find evidence that women who have a say in some of these important household decisions might be better equipped to attenuate the effects of high temperatures on their child/children's health, both when considering the WHZ and child wasting as outcomes. Moreover, we conduct tests using the two other dimensions of the SWPER - intolerance to violence and social independence (see Appendix C.7). We find limited evidence of a mitigating effect of women's empowerment when interacting these respective domains with heat exposure. This suggests that women's ability to make decisions at the household level is likely to be a critical channel between women's empowerment and the protection of child nutrition during times of adversity.

Furthermore, in Appendix C.8, we evaluate the sensitivity of our results according to varying degrees of heat exposure. More specifically, we look at the effect of high temperatures on the child's nutritional outcomes, and the role of women's empowerment as a mitigating factor, for a duration of up to three months following our period of interest. The construction of these alternative heat exposure measures mirrors the methodology used for the temperature variable in our primary specification, which captures children's exposure to average monthly maximum temperatures surpassing 30 °C over a period of three consecutive months. Thus, when we consider the five-month time scale for instance, we are looking at the impact of being exposed to monthly temperatures exceeding 30 °C on average over a period of five consecutive months. The results in Appendix C.8 indicate that higher temperatures are consistently linked to lower WHZ levels across all the exposure periods examined. However, the probability of suffering from wasting only increases up to

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four months of exposure. As for the role of women as a moderating factor, we find that it only becomes significant for the four-month time period. Coupled with the results in Table 3.1, these findings suggest that the protective effect of women with greater instrumental agency becomes notably evident when there is a heightened risk for the child to encounter acute malnutrition - a scenario primarily observed after exposure to prolonged heat lasting three to four consecutive months. Over longer periods, additional coping mechanisms might come into play after an initial reallocation of financial resources, food and care to child nutrition, permitting to limit the probability of child wasting.

The findings in Table 3.1 and Appendix C.8 also demonstrate the lack of a moderating impact of women's empowerment on the WHZ when examining its mean. However, by employing unconditional quantile regressions in the subsequent section, we can analyze how the predictor variables affect different quantiles of the WHZ, thus offering insights into potential heterogeneity.

Dependent variables Variables	WHZ (1)	Wasting (2)	
Heat exposure (>30 $^{\circ}$ C)	-0.119***	0.00629**	
	(0.0184)	(0.00317)	
Decision making	0.00182	0.000887	
Decision making	(0.00102)	(0.000856)	
Heat avposure V Decision making	0.00507	0.00272**	
Heat exposure x Decision making	(0.00397	-0.003/2	
	(0.00/38)	(0.00140)	
	0 0001 5***	0.0010(***	
Child's age (months)	0.0031/***	-0.00186***	
	(0.000255)	(5.03e-05)	
Child's sex (ref: female)	-0.0229***	0.0129***	
	(0.00574)	(0.00120)	
Birth order (count)	0.0812***	-0.00617***	
	(0.00683)	(0.00137)	
Maternal characteristics			
Mother's age (years)	-0.000426	0.000133	
	(0.000472)	(9.99e-05)	
Mother's height (cm)	0.00537***	-0.000535***	
would sheight (chi)	(0.000057)	(0.000333)	
Mathen's advantion (vacua)	(0.000542)	(0.000111)	
Mother's education (years)	0.0124	-0.00204***	
	(0.00109)	(0.000215)	
Household characteristics			
Number of children under five (count)	-0.0253***	0.00150**	
	(0.00352)	(0.000745)	
Sex of household head (ref: female)	0.0206**	-0.000759	
	(0.00937)	(0.00182)	
Source of drinking water (ref: Piped)		. ,	
Well	-0 0240**	0.00121	
	(0.0105)	(0, 00202)	
Other	0.0110	0.00134	
Other	(0.0119)	-0.00134	
Consistantian terms (main Fluch)	(0.0118)	(0.00225)	
Sanitation type (ref: Flush)			
Pit latrine	-0.00620	-0.00432	
	(0.0154)	(0.00306)	
Other	-0.0316*	0.00203	
	(0.0175)	(0.00348)	
Wealth quintiles (ref: Poorest)			
Poorer	0.0193*	-0.00445**	
	(0.0107)	(0.00219)	
Middle	0.0578***	-0.0104***	
	(0.0111)	(0.00224)	
Bicher	0.0566***	-0 0118***	
Idenei	(0.0123)	(0.00245)	
Diaboat	0.0123)	(0.002+3)	
Kichest	0.0900	-0.01/2	
	(0.0154)	(0.00301)	
Residence (ref: rural)	-0.0119	0.000183	
	(0.0120)	(0.00238)	
Climate variable			
Precipitation (ref: <100 mm)			
100-200	0.129***	-0.0193***	
	(0.0220)	(0.00386)	
200-300	0.148***	-0.0241***	
	(0.0331)	(0.00608)	
>300	0.101	-0.0285***	
2000	(0.0668)	(0,00068)	
	(0.0008)	(0.00900)	
Decien V Month	/	/	
	V	V	
Region X Year	\checkmark	\checkmark	
Observations	238,253	238,253	
R-squared	0.089	0.068	

Table 3.1: Heat exposure, nutrition & women's empowerment

Robust standard errors in parentheses clustered at the EA level *** p < 0.01, ** p < 0.05, * p < 0.1*Notes*: Linear model with high dimensional fixed-effects by Correia (2017).

Fixed effects are with respect to the month and year of the interview.

3.5.2 Distributional effects

Results from UQR using RIFs in Table 3.2 first show that elevated temperatures in the three months preceeding the survey have a negative impact on child nutrition, whether we consider the 10th, 50th or 90th quantile (results using bootstrap standard errors, and the effects for quantiles 25 and 75 are respectively in Appendix C.9 and in Appendix C.10). However, it seems that the impact of elevated temperatures on nutrition becomes more pronounced as the child's nutritional status moves higher in the distribution. Specifically, the coefficient associated with heat exposure shows a rising trend across quantiles of the outcome variable. When comparing the 10th and 90th quantiles (columns 1 & 3), we observe that the coefficient for temperature is 0.0608 in the lowest quantile, whereas it increases to 0.173 in the highest quantile. In terms of interpretation, if, for example, the share of instances where temperatures exceed 30 °C increases by 10%, the WHZ of children in the 10th quantile would decrease by 0.608%, compared to 1.73% in the highest quantile⁸.

Children whose nutritional status is lower might already face challenges that constrain their nutrition. The additional effect of a temperature shock may therefore not be as marked. On the other hand, children at the upper end of the distribution in terms of nutrition may benefit from a more diverse and nutritionally rich diet, while being less subject to various diseases and illnesses. By impacting food availability and quality, heat may pose a more important stress to better nourished children, while increasing their chances of suddenly losing weight due to vector-borne and diarrheal diseases. However, despite the magnitude of the impact of heatwave exposure being lower for children who are worse off in terms of nutrition, we anticipate that their likelihood of suffering from wasting is greater in contrast to children with higher WHZ levels.

⁸For binary variables, we can think of the effect as a change in the proportion of individuals/events in a specific group. If the share of heatwave episodes increases by 10% (0.1), the coefficient can be interpreted based on the following computation: (0.1*0.0608)*100 (for the 10th quantile) and (0.01*0.173)*100 for the 90th quantile) (Rios-Avila, 2020).

Additionally, the results presented in Table 3.2 show that women's empowerment only plays a role in mitigating the negative impact of heat on the nutritional status of children within the 10th quantile, at a 1% level of significance. The heightened influence of women's empowerment on lower nutrition levels is further confirmed by the UQR results that utilize the alternative decision making indicator, and the tertiles of the decision making score (see Appendix C.12 and Appendix C.11). In the former case, we observe, similarly, only a moderating effect of women's empowerment in the 10th quantile of the WHZ. In the context of decision making tertiles, the results demonstrate an effect of women's empowerment on both the lowest and highest quantiles; however, the influence is particularly notable amongst children at the lower end of the distribution. Within the 10th quantile, women with greater instrumental agency significantly affect child nutrition during periods of heat, compared to those with lower levels of empowerment, across both the 2nd and 3rd tertiles of decision making. In contrast to the findings at the 90th quantile, where no discernible effect is linked to the 3^{rd} tertile of the decision making score, there appears to be no diminishing returns in terms of empowerment at the 10th quantile.

Some insights into why the impact of empowerment may vary based on the nutritional level of the child could be drawn from our model in Section 3.3. According to the model, during an income shock, the share of resources allocated to child nutrition should increase, especially when the mother possesses greater bargaining power. Following this rationale, if a temperature shock does not significantly impact income, the allocation of resources to child nutrition should remain stable. In such cases, increased bargaining power is likely to have a more limited influence on resource allocation to nutrition during adverse times. Wealthier households, which are likely to have more diversified sources of income, possess the capacity to invest in adaptive strategies and benefit from access to various insurance options, thereby being less affected by shocks. Children with higher a nutritional status are anticipated to reside in more affluent households, where the proportion of resources

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dedicated to nutrition might remain largely unchanged following an adverse event, potentially diminishing the moderating impact of women's involvement in decision making on child nutrition during periods of extreme heat. Appendix C.13 reveals that wealthier households, as classified by the DHS wealth quintiles, exhibit lower levels of wasting compared to households in the lowest quintiles. The average rate of wasting is of 11.4% in the first quintile (poorest households) compared to 7.3% in the last quintile (richest households). In such environments, partners could also have comparable levels of bargaining power. As we examine variations in decision making scores based on household wealth, we observe an increase in women's participation in household decisions as we move up wealth quintiles. Specifically, 45.70% of women are in the 3rd tertile in terms of decision making (highest level) in the fifth wealth quintile compared to 27.91% in the first wealth quintile.

Conversely, for children with lower nutritional levels, decisions favoring health and nutrition, expected to be enhanced by women with higher instrumental agency, may play a crucial role in preventing malnutrition during adversity. These children may reside in households with limited access to insurance options, where strategic choices regarding resource allocation, time, and care become vital after a shock. Women's involvement in adaptation and mitigation could be accentuated in such contexts. In scenarios where extreme temperatures directly affect child nutrition, such as by increasing the prevalence of vector-borne illnesses, rather than through a household-level income shock, several of the aforementioned arguments remain applicable. Indeed, if resources allocated to child health and care are close to optimal, the additional effect of women's empowerment on child nutrition in times of shock may not be as pronounced, especially if differences in bargaining power between partners diminish as we move up the distribution.

Dependent variable: WHZ Variables	Q10 (1)	Q50 (2)	Q90 (3)
Heat exposure (>30 $^{\circ}$ C)	-0.0608*	-0.140***	-0.173***
_	(0.0327)	(0.0190)	(0.0303)
Decision making	-0.0105	0.00113	0.00147
-	(0.00883)	(0.00557)	(0.00959)
Heat exposure X Decision making	0.0402***	0.00431	-0.00736
	(0.0151)	(0.00769)	(0.0123)
Child characteristics	\checkmark	\checkmark	\checkmark
Maternal characteristics	\checkmark	\checkmark	\checkmark
Household characteristics	\checkmark	\checkmark	\checkmark
Climate control	\checkmark	\checkmark	\checkmark
Region X Month	\checkmark	\checkmark	\checkmark
Region X Year	\checkmark	\checkmark	\checkmark
Observations	238,253	238,253	238,253
R-squared	0.069	0.071	0.041

Robust standard errors in parentheses clustered at the EA level *** p<0.01, ** p<0.05, * p<0.1

Notes: Unconditional quantile regression with high dimensional fixed-effects by (Rios-Avila, 2020). Fixed effects are with respect to the month and year of the interview.

3.6 Discussion and conclusion

The aim of this analysis is to explore the extent to which women's empowerment can alleviate the negative impacts of heat on child acute malnutrition in Sub-Saharan Africa. We focus primarily on women's decision making in an attempt to capture their influence on the allocation of household resources, and their choices regarding other matters that could positively affect child nutrition. Evidence suggest that money managed by women is more inclined to be utilized for buying food (Quisumbing and Maluccio, 2003, Porter, 2016) and healthcare (Babu et al., 1993, UNICEF, 2011), particularly in lower-income contexts (McKenna et al., 2019).

Previous studies have investigated the role of women in protecting the health

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of their children following an adverse event. Dimitrova and Muttarak (2020) notably focus on the protective role of maternal education, and find that children born into economically disadvantaged households, but with educated mothers, encounter nearly identical risks of stunting as a result of a weather shock as children born into wealthier households, but to mothers who lack education. Furthermore, they show that better health knowledge and increased utilization of healthcare are the main channels through which mother's education benefits child nutrition. Women's empowerment, in contrast, had a more limited influence.

With respect to this work, our research first examines how specific dimensions of women's empowerment can help alleviate the detrimental effects of heat on child nutrition. We base our analysis on 25 countries in Sub-Saharan Africa for which we have information over several years. To measure women's empowerment, we use the SWPER indicator, which permits to account for the multidimensional nature of the latter. Although we primarily focus on women's decision making, we also look at the influence of other dimensions, including intolerance to violence and social independence.

As a second step, we examine how effects might vary according to the level of child nutrition. To do so, we estimate unconditional quantile regressions (UQR) with high dimensional fixed effects. We specifically look at the varying effect of heat, and the moderating impact of women's empowerment, according to whether the child is positioned at the 10th, 50th or 90th quantile with respect to nutrition, as measured by the WHZ. This analysis allows to shed light on the vulnerability of children to shocks at different positions in the nutritional distribution, as well on the role of women's empowerment as a mitigating factor according to children's distinct nutritional requirements.

In line with the growing body of evidence on the linkages between weather anomalies and malnutrition in children, we find that exposure to high average monthly temperatures is negatively associated with children's WHZ, and positively correlated with the probability of being wasted. Furthermore, we provide evidence

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that, for a given level of education, women with a higher level of decision power can play a crucial role in protecting the nutrition of children who have been exposed to elevated temperatures over extended periods. These results align with our conceptual model, which illustrates that in households where the mother has an increased preference for child nutrition compared to her partner, the allocation of resources to child nutrition will experience a more substantial rise following a shock when the mother possesses greater bargaining power. We also show that other domains of empowerment, such as intolerance to violence and social independence, do not necessarily explain our results. These findings seem to corroborate that the moderating impact of women's empowerment during heat stress primarily manifests through greater instrumental agency.

Additionally, we find that the protective role of women with greater decision power is especially pronounced amongst children with the lowest WHZ levels. While women's empowerment is primordial for the nutrition of all children (Santoso et al., 2019), these results suggest that in more resource-constrained households - where adaptive capacity is limited and shocks could have more devastating consequenceswomen's ability to make choices at the household level, on matters such as the allocation of food and money, alongside considerations for children care and health, could be particularly crucial in addressing the immediate health challenges faced by the most vulnerable children.

A few considerations should nevertheless be highlighted, namely with respect to our measure of women's empowerment, the SWPER. First, as underlined by Ewerling et al. (2020), there are several elements known to enable or limit empowerment that are not accounted for in the SWPER. For example, the decision making domain, on which our analysis primarily focuses, evaluates the extent of women's control over certain household matters but it does not encompass the aspect of choice, nor the potential risks of facing sanctions or backlash due to the decisions taken (Ewerling et al., 2020). Other important elements for empowerment that are not considered in the SWPER include personal asset ownership, engagement in economic activities, participation in governance mechanisms and opportunities, as well as rights to resources and other types of discrimination targeting women (Ewerling et al., 2017, 2020). While variables related to some of these aspects are progressively being incorporated into DHS, they are only available in a limited number of recent surveys, which would consequently restrict the range of countries for which the SWPER could be computed (Ewerling et al., 2020). However, whenever possible with the available data, future research should strive to encompass the broad spectrum of dimensions that constitute women's empowerment. Additionally, another limitation of the SWPER is that it only applies to women who are either married or in a union, thereby disregarding unpartnered women. Consequently, in some countries, an important share of women are excluded from the index (Ewerling et al., 2017, 2020). Yet, many of these unpartnered women could still be empowered (Ewerling et al., 2017), which suggests that our analysis might underestimate empowerment levels. Nonetheless, as underlined in (Ewerling et al., 2017), these unmarried women could also comprise adolescents, as well as disabled women and sex workers, who are amongst the most marginalized and disempowered. In such cases, our study may actually overestimate empowerment levels. These limitations underscore the necessity for national health surveys to expand their coverage to include information on empowerment for unpartnered women.

With these aspects in mind, our study carries several implications for policymakers and other stakeholders. Firstly, considering the heightened vulnerability of children to heat, our analysis emphasizes the need for targeted nutrition interventions aimed at mitigating both the immediate and long-term impacts of climate change on children. Secondly, our research contributes additional evidence on the potential for women to assume pivotal roles in coping and adaptation processes. Increasing women's empowerment, especially in households prone to hardship, can improve the allocation of limited resources towards the well-being of children. Acknowledging the importance of empowering women and addressing gender inequality is therefore paramount in the broader effort to mitigate the impacts of climate

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change. To this end, initiatives to enhance women's access to financial resources, credit, and land rights, alongside investments in their education and skill development, may be critical. Equally central is the integration of gender perspectives into climate change policies and strategies. This approach appears essential not only for understanding how climate change affects men and women differently but also for designing interventions that address the specific needs and capacities of women.

Main results

The dissertation focuses on the interactions between forests, weather shocks and food security and nutrition in developing countries. In light of the significant threat climate change poses to food security and the constrained access of agricultural households in developing countries to formal insurance mechanisms, the first chapter of the thesis focuses on the role of natural capital in households' ability to resist weather-related shocks in Malawi. Specifically, the objective is to explore the effectiveness of forests as a safety net for food security, especially in light of other insurance alternatives. The results of this analysis suggest that forests can mitigate the negative impacts of a weather shock on households' dietary diversity both in the absence of options, and when other alternatives are available. Forest resources might, hence, either be used as a safety net as an option of last resort, or in complement to other options, potentially limiting the reliance on costly coping strategies (Mulungu and Kilimani, 2023).

The use of forests as a natural insurance raises important questions regarding the balance between providing forest access to vulnerable communities and conserving natural resources. In practice, the co-management of natural resources has the potential to align the needs of people with those of the environment. Despite anticipated benefits, evidence on the effectiveness of these schemes in achieving their dual objective varies. The second chapter of the dissertation aims to enhance understanding of factors influencing co-management outcomes by assessing the effectiveness of Malawi's national forest co-management program, the Improved Forest Management for Sustainable Livelihoods Programme (IFMSLP), in meeting poverty alleviation and conservation goals. Our findings suggest that the IFMSLP has increased rather than reduced poverty with effects that seem to dissipate overtime. This negative effect is especially pronounced amongst households with fewer livelihood options and a high dependence on natural resources. When it comes to forests, we find, overall, no effect of the IFMSLP on deforestation.

Lastly, within the framework of the dissertation's third chapter, we investigate how increased levels of women's empowerment could potentially reduce a child's vulnerability to undernutrition after exposure to heat in several Sub-Saharan countries. Our primary focus is on women's decision making as we seek to capture how their involvement in household decisions may influence the share of household resources allocated to child nutrition in the aftermath of a shock. Our empirical results confirm that women with greater instrumental agency can play a key role in protecting child nutrition after exposure to extended periods of heat. This moderating effect appears to be especially concentrated amongst children with the lowest nutrition levels. These findings suggest that women's ability to make choices at the household level on matters such as the allocation of food and money, alongside considerations for children care and health, could be particularly crucial in addressing the immediate health challenges faced by the most vulnerable children.

All three chapters of the dissertation mobilize empirical methods to address the various research questions. In this context, we make use of two main types of household data. In the first two chapters, we mobilize a nationally representative household panel survey for Malawi that enables to follow the same households (including split-off households) over several years. This approach notably facilitates the adoption of empirical methods capable of accounting for the bias that arises from omitted variables that do not vary overtime. Furthermore, the availability of GPS coordinates in this household database permits the integration of remote sensing information at the level of the EA. Within the framework of the first chapter, this allows to more precisely connect weather shocks with household adaptation strategies linked to the use of NTFPs. In the second chapter, the added spatial information allows to determine the exact location of Forest Reserves with respect to the location of households, making it possible to conduct a programme evaluation of forest co-management in Malawi, while considering both poverty and forest-related outcomes. Regarding the final chapter, it employs a comprehensive database that combines individual and household level information across a wide

panel of Sub-Saharan countries, and over several years. This enables us to capture both spatial and temporal variations effectively. In addition, the dataset includes information on temperature and precipitation levels within a specified range around household cluster locations, allowing us to explore potential connections between weather shocks and nutritional outcomes.

The dissertation has three main contributions. Firstly, in exploring households' responses to adverse weather events, the thesis contributes to the literature on the co-benefits associated with environmental protection and empowering women and girls in developing countries. Indeed, by underscoring the effectiveness of forests as a safety net for food security in the aftermath of a weather shock, we highlight the significant advantages for human well-being and livelihoods that stem from preserving forest ecosystems. These positive contributions complement the recognized roles of forests in climate change mitigation and biodiversity conservation, amongst others. Furthermore, our research adds to the existing literature on the co-benefits associated with women's empowerment by illustrating how increased instrumental agency amongst women can lead to positive outcomes for child nutrition during times of adversity. To this date, there appears to be limited empirical evidence on the potential benefits of increased women's decision making for weather shock mitigation over varying spatial and temporal dimensions.

As a second contribution, the dissertation explores heterogeneous effects according to household and/or individual characteristics both in relation to responses to weather shocks and in evaluating the effects of forest co-management on wellbeing and conservation. By adopting this approach, we first add to the literature on the natural insurance role of forests by offering further insights into the extent to which they are relied upon amidst other alternatives available to households. Additionally, considering various household and/or individual profiles provides the possibility to account for population sub-groups for which the effects of an event, strategy, or policy may vary. These considerations notably allow us, in the second chapter, to contribute to deepening understanding of the potential path-

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ways through which co-management might influence poverty and forest-related outcomes, which is, to date, lacking in the literature. Furthermore, in the third chapter, they enable us to identify groups of individuals that are the most likely to benefit from certain coping strategies in the aftermath of a shock, while offering insights into contexts where disparities in bargaining power between partners are expected to be significant, and where empowering women should hence be prioritized.

Lastly, the thesis' emphasis on food security and nutrition enhances our comprehension of the connections between the environment and well-being, as well as between weather anomalies and well-being, both individually and collectively, from both an input and output perspective. In contrast to solely examining monetary measures, incorporating outcomes pertaining to food security and nutrition may offer a more comprehensive understanding of household and individual welfare, particularly in contexts marked by limited market access, subsistence agriculture, resource-dependence, and reliance on informal activities. In the first two chapters, exploring household dietary diversity allows us to account for the role of forests in providing a diverse range of food options to households, which can occur through both market and non-market mechanisms. Furthermore, within the context of the second chapter, examining food security in conjunction with asset value and incomes enables us to address the multi-faceted nature of poverty. This approach also sheds light on the interconnectedness between food security and various economic aspects such as incomes and consumption patterns. Regarding the final chapter, the focus on nutrition amongst young children offers a direct approach to assess the health implications linked with weather anomalies, especially within a particularly vulnerable population group. Moreover, it allows us to explore the role of women in addressing these challenges, given their central role in childcare and household decision making.

Policy implications

Overall, the findings of this thesis advocate for reflections on co-benefits within policy frameworks. Specifically, the results from the first chapter highlight the importance of preserving forest environments for human well-being. Emphasizing conservation is also key considering that the use of forests as a safety net raises important questions regarding the sustainable management of forest resources. It is therefore primordial for policies to strive to reconcile human needs with environmental conservation. Precisely, this could entail maintaining local communities' access to forests while promoting their sustainable utilization, as participatory forest management schemes aim to achieve.

Nevertheless, our evaluation of forest co-management initiatives in Malawi reveals that programs explicitly aimed at enhancing livelihoods and conservation may not consistently yield positive outcomes on both fronts. These findings align with previous research at the household level which suggest mixed effects when it comes to the outcomes of co-management. The second chapter findings hence suggest that several pre-conditions likely need to be met to ensure successful forest co-management outcomes. Notably, it may be especially important for policies promoting reliance on environmental income to carefully account for the alternative income-generating opportunities available to targeted communities, given the typically low returns from resource extraction and utilization. Furthermore, consideration of the broader context in which these communities operate also appears necessary, including factors such as the availability of markets for the promoted resources, the initial configuration of forest rights, and potential barriers that may limit communities' ability to fully benefit from co-management and its related activities.

Lastly, the third chapter's findings shed light on the critical role of empowering women in promoting child health and resilience amidst the challenges of climate

change. This emphasizes the necessity for policymakers and other stakeholders to adopt an integrated approach to women's empowerment, recognizing its multifaceted benefits. Furthermore, it suggests that initiatives aimed at mitigating the effects of climate change on vulnerable populations, such as children, must explicitly recognize the importance of empowering women and addressing gender disparities. These considerations are key to leverage women's capabilities to contribute to adaptation and mitigation processes while addressing their specific needs.

Furthermore, the heterogeneity across households and individuals revealed in our analyses highlight the need for targeted interventions. These interventions are primordial not only to enhance populations' resilience to climate change but also to formulate effective livelihood-improving policies. Our findings notably shed light on specific demographic groups, including children and natural resourcedependent communities, that are particularly susceptible to environmental stressors and socioeconomic challenges. Tailoring policies and programs to address the unique needs of these specific population sub-groups, while directing resources and efforts toward tackling disparities and fostering equity in outcomes, appears essential for ensuring positive outcomes among vulnerable communities.

Limitations and research perspectives

The three chapters of the dissertation mobilize large-scale household surveys that use GPS technology to capture the location of EAs, as well household and agricultural plots. This approach notably facilitates the integration of survey data with remote sensing information, as underlined earlier. However, since these datasets are intended for public dissemination, survey programs face the challenge of balancing data accuracy with privacy protection (Michler et al., 2022). Consequently, while precise GPS coordinates are recorded, the data undergoes "spatial anonymization" before its public release to protect confidentiality (Michler et al., 2022). The technique adopted by DHS and LSMS involves the random offset of precise EA co-

ordinates by distances ranging from zero to two kilometers in urban areas and two to five kilometers in rural areas, with a displacement of up to ten kilometers for one percent of rural regions (Blankespoor et al., 2021). Potential mismeasurement can, therefore, be introduced when combining these survey data with geospatial information, as done in this dissertation. Although Michler et al. (2022) find limited evidence suggesting that privacy protection methods employed by large-scale household surveys, such as the LSMS-ISA, affect the accuracy of analyses involving remote sensing weather data, the authors highlight that studies, for which weather data is a key component of the identification strategy, should consider demonstrating robustness of results by using different weather metrics. Furthermore, for enhanced accuracy, future research could consider adopting methods that aim at correcting the potential errors introduced by cluster location displacement. While relatively coarse remote sensing data could potentially remain unaffected by these displacements, distance-based covariates, as well as finer resolution cluster-level variables, are likely to be affected by them. Various methodological recommendations, tailored to the type of analysis conducted with geospatial data, can for instance be found in Perez-Heydrich et al. (2013).

Moreover, the thesis faces limitations in data availability regarding forest products and forest-related activities. In the context of the first chapter, access to detailed information on the specific types and quantities of forest products collected, along with information on forest-related activities, the proportion of income generated from these products, and the share directly consumed, would greatly enhance our ability to measure households' reliance on forest and environmental resources after a weather shock, while also allowing us to assess dependence prior to the adverse event. The National Household Forest Survey 2018-2019 for Liberia, conducted by the World Bank and the Liberian Government, is an example of a dataset that provides valuable information on the role of forest products in supporting rural livelihoods, including during periods of food insecurity and in response to shocks and crises. However, this dataset currently covers only one year and is limited to

a single country, restricting its broader applicability. Research focused on better understanding the contribution of forests to welfare and livelihoods would considerably benefit from the widespread adoption of such questionnaires across multiple countries, and within the framework of longitudinal household surveys, such as those conducted by the LSMS-ISA. Similar to the first chapter, the second chapter would be enriched by comprehensive data on forest-related activities, enterprises, and resource quantities and prices, as these elements would enable to more precisely identify how co-management activities impact livelihoods and conservation. Future empirical research could notably examine local firewood prices to gain insights into household resource extraction levels and associated economic returns, enhancing insights into the relationship between resource extraction, poverty alleviation, and forest outcomes.

Finally, this thesis does not account for the retroactive effects of climate on forests. In the first chapter, we consequently overlook how past climate-related shocks might have impacted tree health and growth patterns, potentially affecting forests' long-term capacity to provide a natural insurance for communities adjacent to forests. This gap highlights the necessity for future research to integrate insights from biophysical sciences. Doing so would enable to complement studies that focus on the short term with studies that adopt a longer term perspective. Furthermore, an aspect omitted throughout the thesis, and which could warrant further investigation, is the explicit consideration of the social, cultural, economic and political context within the framework of questions dealing with nutrition. These dimensions are fundamental causes of undernutrition, as outlined by UNICEF's conceptual framework of 1990, and are also vulnerable to climate change. Weather-related shocks can notably exacerbate conflicts, jeopardizing household socioeconomic resources and subsequently impacting food security and nutrition. Additionally, as highlighted in (Collier et al., 2009), the deterioration of health conditions that occurs during conflicts is long-lasting, suggesting further challenges in addressing malnutrition in conflict-affected regions.
Bibliography

- Abay, K. A. and Jensen, N. D. (2020). Access to markets, weather risk, and livestock production decisions: Evidence from Ethiopia. *Agricultural Economics*, 51(4):577–593.
- Abman, R. and Carney, C. (2020). Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in Malawi. *Journal of Envi ronmental Economics and Management*, 103:102342.
- Acosta, A., Nicolli, F., and Karfakis, P. (2021). Coping with climate shocks: The complex role of livestock portfolios. *World Development*, 146:105546.
- Adger, W. N. and Winkels, A. (2014). Vulnerability, poverty and sustaining wellbeing. In *Handbook of sustainable development*, pages 206–216. Edward Elgar Publishing.
- Alderman, H. and Headey, D. D. (2017). How important is parental education for child nutrition? *World development*, 94:448–464.
- Alderman, H. and Paxson, C. H. (1994). Do the Poor Insure? A Synthesis of the Literature on Risk and Consumption in Developing Countries, page 48–78. Palgrave Macmillan UK.
- Alemayehu, A. and Bewket, W. (2017). Smallholder farmers' coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia. *Local Environment*, 22(7):825–839.

- Alsop, R., Bertelsen, M. F., and Holland, J. (2006). *Empowerment in practice: From analysis to implementation*. World Bank Publications.
- Andrews, J. and Mulder, M. B. (2022). Forest income and livelihoods on Pemba: A quantitative ethnography. *World Development*, 153:105817.
- Angelsen, A. (1999). Agricultural expansion and deforestation: modelling the impact of population, market forces and property rights. *Journal of Development Economics*, 58(1):185–218.
- Angelsen, A. (2007). Forest cover change in space and time: combining the von Thünen and forest transition theories, volume 4117. World Bank Publications.
- Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S.,
 Börner, J., Smith-Hall, C., and Wunder, S. (2014). Environmental income and rural livelihoods: a global-comparative analysis. *World development*, 64:S12–S28.
- Angelsen, A. and Wunder, S. (2003). *Exploring the forest-poverty link: Key concepts, issues and research implications*. Bogor, Indonesia: CIFOR, Center for International Forestry Research, Bogor, Indonesia.
- Arthur, S. S., Nyide, B., Soura, A. B., Kahn, K., Weston, M., and Sankoh, O. (2015).
 Tackling malnutrition: a systematic review of 15-year research evidence from INDEPTH health and demographic surveillance systems. *Global Health Action*, 8(1):28298.
- Ashley, C., Carney, D., et al. (1999). *Sustainable livelihoods: Lessons from early experience*, volume 7. Department for International Development London.
- Ashraf, M. and Routray, J. K. (2013). Perception and understanding of drought and coping strategies of farming households in north-west Balochistan. *International Journal of Disaster Risk Reduction*, 5:49–60.
- Ashton, P. J. (2002). Avoiding conflicts over Africa's water resources. *AMBIO: A Journal of the Human Environment*, 31(3):236–242.

- Babu, S. C., Thirumaran, S., and Mohanam, T. (1993). Agricultural productivity, seasonality and gender bias in rural nutrition: Empirical evidence from South India. *Social science & medicine*, 37(11):1313–1319.
- Baker, R. E. and Anttila-Hughes, J. (2020). Characterizing the contribution of high temperatures to child undernourishment in Sub-Saharan Africa. *Scientific Reports*, 10(1).
- Bala, G., Caldeira, K., Wickett, M., Phillips, T., Lobell, D., Delire, C., and Mirin, A. (2007). Combined climate and carbon-cycle effects of large-scale deforestation. *Proceedings of the National Academy of Sciences*, 104(16):6550–6555.
- Baland, J. and Platteau, J. (1996). *Halting degradation of natural resources: is there a role for rural communities?* Food and Agriculture Organization (FAO).
- Baland, J.-M. and Francois, P. (2005). Commons as insurance and the welfare impact of privatization. *Journal of Public Economics*, 89(2-3):211–231.
- Bandyopadhyay, S., Kanji, S., and Wang, L. (2012). The impact of rainfall and temperature variation on diarrheal prevalence in Sub-Saharan Africa. *Applied Geography*, 33:63–72.
- Banerjee, A. and Duflo, E. (2011). *Poor economics: A radical rethinking of the way to fight global poverty*. Public Affairs, New York.
- Barbier, E. (2010). Poverty, development, and environment. *Environment and Development Economics*, 15:635–660.
- Barbier, E. and Hochard, J. (2019). Poverty-Environment Traps. *Environmental and Resource Economics*, 74:1239–1271.
- Barrett, C., Garg, T., and McBride, L. (2016). Well-being dynamics and poverty traps. *Annual Review of Resource Economics*, 8:303–327.

- Barrett, C., Travis, A., and Dasgupta, P. (2011). On biodiversity conservation and poverty traps. *Proceedings of the National Academy of Sciences*, 108(34):13907–13912.
- Bati, B. M. (2014). Climate change, cattle herd vulnerability and food insecurity: Adaptation through livestock diversification in the Borana pastoral system of Ethiopia. Doctoral dissertation, Kommunikations-, Informations-und Medienzentrum der Universität Hohenheim.
- Batliwala, S. (1994). The meaning of women's empowerment: New concepts from action. *Population policies reconsidered: Health, empowerment and rights,* 17:127–138.
- Becker, S., Fonseca-Becker, F., and Schenck-Yglesias, C. (2006). Husbands' and wives' reports of women's decision-making power in Western Guatemala and their effects on preventive health behaviors. *Social Science & Medicine*, 62(9):2313–2326.
- Behrman, J. R. and Skoufias, E. (2004). Correlates and determinants of child anthropometrics in Latin America: background and overview of the symposium. *Economics & Human Biology*, 2(3):335–351.
- Béné, C., Waid, J., Jackson-deGraffenried, M., Begum, A., Chowdhury, M., Skarin,
 V., Rahman, A., Islam, N., Mamnun, N., Mainuddin, K., et al. (2015). Impact
 of climate-related shocks and stresses on nutrition and food security in selected
 areas of rural Bangladesh. *Dhaka World Food Programme*, 3.
- Benson, T. (2021). *Disentangling food security from subsistence agriculture in Malawi Synopsis*. International Food Policy Research Institute.
- Berman, R. J., Quinn, C. H., and Paavola, J. (2015). Identifying drivers of household coping strategies to multiple climatic hazards in Western Uganda: implications for adapting to future climate change. *Climate and Development*, 7(1):71–84.

- Bezabih, M. and Sarr, M. (2012). Risk preferences and environmental uncertainty: Implications for crop diversification decisions in Ethiopia. *Environmental and Resource Economics*, 53:483–505.
- Bhattacharya, A., Pal, B., Mukherjee, S., and Roy, S. K. (2019). Assessment of nutritional status using anthropometric variables by multivariate analysis. *BMC public health*, 19:1–9.
- Black, R. E., Allen, L. H., Bhutta, Z. A., Caulfield, L. E., De Onis, M., Ezzati, M., Mathers, C., and Rivera, J. (2008). Maternal and child undernutrition: global and regional exposures and health consequences. *The lancet*, 371(9608):243–260.
- Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., De Onis, M., Ezzati, M., Grantham-McGregor, S., Katz, J., Martorell, R., et al. (2013).
 Maternal and child undernutrition and overweight in low-income and middle-income countries. *The Lancet*, 382(9890):427–451.

Blackden, M. and Wodon, Q. (2006). Gender, time use, and poverty: Introduction.

- Blankespoor, B., Croft, T., Dontamsetti, T., Mayala, B., and Murray, S. (2021). Spatial anonymization: Guidance note prepared for the Inter-Secretariat working group on household surveys. UN Intersecretariat Working Group on Household Surveys Task Force on Spatial Anonymization in Public Use Household Survey Datasets.
- Blom, S., Ortiz-Bobea, A., and Hoddinott, J. (2022). Heat exposure and child nutrition: Evidence from West Africa. *Journal of Environmental Economics and Management*, 115:102698.
- Bloom, S. S., Wypij, D., and Das Gupta, M. (2001). Dimensions of women's autonomy and the influence on maternal health care utilization in a north Indian city. *Demography*, 38:67–78.

- Bo, M., Guo, Y.-q., Tao, H.-b., Liu, G.-z., Li, S.-k., and Pu, W. (2015). Speipmbased research on drought impact on maize yield in North China Plain. *Journal of Integrative Agriculture*, 14(4):660–669.
- Bonan, G. B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *science*, 320(5882):1444–1449.
- Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting Event Study Designs: Robust and Efficient Estimation. arxiv:2108.12419. https://arxiv.org/abs/ 2108.12419.
- Bouwman, T., Andersson, J., and Giller, K. (2021). Herbicide induced hunger? Conservation agriculture, ganyu labour and rural poverty in Central Malawi. *The Journal of Development Studies*, 57(2):244–263.
- Boyle, E. H., King, M. L., Garcia, S., Culver, C., and Bourdeaux, J. (2020). Contextual data in IPUMS DHS: physical and social environment variables linked to the Demographic and Health Surveys. *Population and environment*, 41:529–549.
- Brack, D. (2019). Forests and climate change. In Proceedings of Background Study Prepared for the Fourteenth Session of the United Nations Forum on Forests. New York, NY, USA: United Nations Forum on Forests.
- Brooks, N. (2003). Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for climate change research working paper*, 38(38):1–16.
- Brown, M. E., Grace, K., Shively, G., Johnson, K. B., and Carroll, M. (2014). Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change. *Population and environment*, 36(1):48–72.
- Bryan, E., Deressa, T. T., Gbetibouo, G. A., and Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science & Policy*, 12(4):413–426.

- Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., and Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. *Journal of environmental management*, 114:26–35.
- Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.
- Call, M., Gray, C., and Jagger, P. (2019). Smallholder responses to climate anomalies in rural Uganda. *World Development*, 115:132–144.
- Caminade, C. and Jones, A. (2016). Malaria in a warmer west Africa. *Nature Climate Change*, 6(11):984–985.
- Campbell, B. M. E. (1996). The miombo in transition: woodlands and welfare in Africa. Technical report, CIFOR.
- Cardinael, R., Deheuvels, O., Leroux, L., Subervie, J., Suwa-Eisenmann, A., Bessou,
 C., Bouquet, E., Catry, T., Chikowo, R., Corbeels, M., et al. (2022). Food security and natural resources: diversification strategies. In : Sustainable food systems for food security. Need for combination of local and global approaches. Thomas Alban (ed.), Alpha Arlène (ed.), Barczak Aleksandra (ed.), Zakhia-Rozis Nadine (ed.). Versailles : Ed. Quae, 171-185. (Synthèses : Quae) ISBN 978-2-7592-3575-9.
- Carlson, G. J., Kordas, K., and Murray-Kolb, L. E. (2015). Associations between women's autonomy and child nutritional status: a review of the literature. *Maternal & child nutrition*, 11(4):452–482.
- Carlton, E. J., Woster, A. P., DeWitt, P., Goldstein, R. S., and Levy, K. (2016). A systematic review and meta-analysis of ambient temperature and diarrhoeal diseases. *International journal of epidemiology*, 45(1):117–130.
- Carter, M. R. and Lybbert, T. J. (2012). Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, 99(2):255–264.

- Caulfield, L. E., Richard, S. A., Rivera, J. A., Musgrove, P., and Black, R. E. (2006). Stunting, wasting, and micronutrient deficiency disorders. *Disease Control Priorities in Developing Countries. 2nd edition.*
- Challinor, A., Slingo, J., Turner, A., and Wheeler, T. (2006). Indian monsoon: Contribution to the stern review. *Stern review on the economics of climate change*.
- Challinor, A., Wheeler, T., Garforth, C., Craufurd, P., and Kassam, A. (2007). Assessing the vulnerability of food crop systems in Africa to climate change. *Climatic change*, 83:381–399.
- Chang, C. Y., Trehan, I., Wang, R. J., Thakwalakwa, C., Maleta, K., Deitchler, M., and Manary, M. J. (2013). Children successfully treated for moderate acute malnutrition remain at risk for malnutrition and death in the subsequent year after recovery. *The Journal of nutrition*, 143(2):215–220.
- Chankrajang, T. (2019). State-community property-rights sharing in forests and its contributions to environmental outcomes: Evidence from Thailand's community forestry. *Journal of Development Economics*, 138:261–273.
- Checkley, W., Epstein, L. D., Gilman, R. H., Figueroa, D., Cama, R. I., Patz, J. A., and Black, R. E. (2000). Effects of Ei Niño and ambient temperature on hospital admissions for diarrhoeal diseases in Peruvian children. *The Lancet*, 355(9202):442–450.
- Chipompha, N. (1985). Some mushrooms of Malawi. In: Forestry Research Record,Vol. 63, Forest Research Institute of Malawi Government Printer, Malawi.
- Christensen, J. H., Hewitson, B., Busuioc, A., Chen, A., Gao, X., Held, I., Jones, R., Kolli, R. K., Kwon, W.-T., Laprise, R., et al. (2007). Regional climate projections. chapter 11.
- Christian, A. K., Marquis, G. S., Colecraft, E. K., Lartey, A., and Soueida, R. (2019). Household food insecurity but not dietary diversity is associated with children's

mean micronutrient density adequacy in rural communities across Ghana. *Nu*-*trition*, 65:97–102.

- Clarke, J., Cavendish, W., and Coote, C. (1996). Rural households and miombo woodlands: use, value and management. In: Campbell, B.N., Ed., The Miombo in Transition: Woodlands and Welfare in Africa, Centre for International Forestry Research, Bogor, 101-135.
- Cohn, A. S., Newton, P., Gil, J. D., Kuhl, L., Samberg, L., Ricciardi, V., Manly, J. R., and Northrop, S. (2017). Smallholder agriculture and climate change. *Annual Review of Environment and Resources*, 42:347–375.
- Collier, P., Chauvet, L., Hegre, H., et al. (2009). The security challenges in conflict prone countries. Technical report, Paris Dauphine University.
- Collins, J. M. (2011). Temperature variability over Africa. *Journal of climate*, 24(14):3649–3666.
- Conde-Agudelo, A. (2000). Maternal morbidity and mortality associated with interpregnancy interval: cross sectional study. *BMJ*, 321(7271):1255–1259.
- Cooper, M. W., Brown, M. E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., Silva, J., and Zvoleff, A. (2019). Mapping the effects of drought on child stunting. *Proceedings of the National Academy of Sciences*, 116(35):17219–17224.
- Cooper, P. J., Dimes, J., Rao, K., Shapiro, B., Shiferaw, B., and Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? *Agriculture, ecosystems & environment*, 126(1-2):24–35.
- Cooper, S. J. and Wheeler, T. (2016). Rural household vulnerability to climate risk in Uganda. *Regional Environmental Change*, 17(3):649–663.
- Corbett, J. (1988). Famine and household coping strategies. *World development*, 16(9):1099–1112.

- Correia, S. (2017). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. *Unpublished manuscript*, 4:2.
- Coulibaly, J. Y., Gbetibouo, G. A., Kundhlande, G., Sileshi, G. W., and Beedy, T. L. (2015). Responding to crop failure: Understanding farmers' coping strategies in Southern Malawi. *Sustainability*, 7(2):1620–1636.
- Cowell, F. A. and Flachaire, E. (2015). Statistical methods for distributional analysis. In *Handbook of income distribution*, volume 2, pages 359–465. Elsevier.
- Croson, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature*, 47(2):448–474.
- Cunningham, K., Ruel, M., Ferguson, E., and Uauy, R. (2015). Women's empowerment and child nutritional status in South Asia: a synthesis of the literature. *Maternal & child nutrition*, 11(1):1–19.
- Cuthbert, M. O., Taylor, R. G., Favreau, G., Todd, M. C., Shamsudduha, M., Villholth, K. G., MacDonald, A. M., Scanlon, B. R., Kotchoni, D. V., Vouillamoz, J.-M., et al. (2019). Observed controls on resilience of groundwater to climate variability in sub-Saharan Africa. *Nature*, 572(7768):230–234.
- Davenport, F., Grace, K., Funk, C., and Shukla, S. (2017). Child health outcomes in sub-Saharan Africa: a comparison of changes in climate and socio-economic factors. *Global Environmental Change*, 46:72–87.
- De Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9):2964–96.
- De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American economic review*, 110(9):2964–2996.

- De Onis, M., Blossner, M., Organization, W. H., et al. (1997). WHO global database on child growth and malnutrition. Technical report, World Health Organization.
- Delacote, P. (2007). Agricultural expansion, forest products as safety nets, and deforestation. *Environment and Development Economics*, 12(2):235–249.
- Delacote, P. (2009). Commons as insurance: safety nets or poverty traps? *Environment and Development Economics*, 14(3):305–322.
- Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.
- Dercon, S. (2002). Income risk, coping strategies, and safety nets. *The World Bank Research Observer*, 17(2):141–166.
- Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., and Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the nile basin of Ethiopia. *Global environmental change*, 19(2):248–255.
- Deressa, T. T., Ringler, C., and Hassan, R. M. (2010). Factors affecting the choices of coping strategies for climate extremes. *The case of farmers in the Nile Basin of Ethiopia IFPRI Discussion Paper*, 1032.
- Desbureaux, S. and Damania, R. (2018). Rain, forests and farmers: Evidence of drought induced deforestation in Madagascar and its consequences for biodiversity conservation. *Biological Conservation*, 221:357–364.
- Deville, J.-C. (1999). Variance estimation for complex statistics and estimators: linearization and residual techniques. *Survey methodology*, 25(2):193–204.
- Dimitrova, A. and Muttarak, R. (2020). After the floods: Differential impacts of rainfall anomalies on child stunting in India. *Global Environmental Change*, 64:102130.

- Doctor, H. V. and Nkhana-Salimu, S. (2017). Trends and determinants of child growth indicators in Malawi and implications for the sustainable development goals. *AIMS Public Health*, 4(6):590.
- Duflo, E. (2012). Women empowerment and economic development. *Journal of Economic literature*, 50(4):1051–1079.
- Dunne, J. P., Stouffer, R. J., and John, J. G. (2013). Reductions in labour capacity from heat stress under climate warming. *Nature Climate Change*, 3(6):563–566.
- EC-FAO (1998). Data Collection and Analysis for Sustainable Forest Management in ACP Countries Linking National and International Efforts.
- Eckel, C. C. and Grossman, P. J. (1998). Are women less selfish than men? Evidence from dictator experiments. *The economic journal*, 108(448):726–735.
- Efron, B. (1982). *The Jackknife, the Bootstrap and Other Resampling Plans*. Society for Industrial and Applied Mathematics.
- Elum, Z. A., Modise, D. M., and Marr, A. (2017). Farmer's perception of climate change and responsive strategies in three selected provinces of South Africa. *Climate Risk Management*, 16:246–257.
- Engel, S., Palmer, C., and Pfaff, A. (2013). On the endogeneity of resource comanagement: Theory and evidence from Indonesia. *Land Economics*, 89(2):308–29.
- Engle, P. L., Menon, P., and Haddad, L. (1999). Care and nutrition: concepts and measurement. *World development*, 27(8):1309–1337.
- European Environment Agency (2015). *Water-retention potential of Europe's forests: a European overview to support natural water retention measures*. Publications Office.
- Ewerling, F., Lynch, J. W., Victora, C. G., van Eerdewijk, A., Tyszler, M., and Barros,A. J. (2017). The SWPER index for women's empowerment in Africa: develop-

ment and validation of an index based on survey data. *The Lancet Global Health*, 5(9):e916–e923.

- Ewerling, F., Raj, A., Victora, C. G., Hellwig, F., Coll, C. V., and Barros, A. J. (2020).SWPER Global: A survey-based women's empowerment index expanded from Africa to all low-and middle-income countries. *Journal of global health*, 10(2).
- FAO (1996). The State of Food and Agriculture. Retrieved from: http://www.fao. org/3/w1358e/w1358e00.htm.
- FAO (2010). Nutrition Country Profiles: Malawi. Retrieved from: http://www.fao.org/ag/agn/nutrition/mwi_en.stm.
- FAO & IIASA (2007). Mapping biophysical factors that influence agricultural production and rural vulnerability. Rome, FAO.
- FAO, IFAD & WFP (2015). The State of Food Insecurity in the World 2015. Meeting the 2015 international hunger targets: taking stock of uneven progress. FAO, Rome.
- FAO, IFAD, UNICEF, WFP and WHO (2018). The State of Food Security and Nutrition in the World 2018. Building climate resilience for food security and nutrition.Rome, FAO. Licence: CC BY-NC-SA 3.0 IGO.
- FAO, IFAD, UNICEF, WFP and WHO (2020). The State of Food Security and Nutrition in the World 2020. Transforming food systems for affordable healthy diets. Rome, FAO.
- Field, C. B. and Barros, V. R. (2014). *Climate change 2014-Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press.
- Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, 77(3):953–973.
- Fisher, M. (2004). Household welfare and forest dependence in southern Malawi. *Environment and Development Economics*, 9(2):135–154.

- Fisher, M., Chaudhury, M., and McCusker, B. (2010). Do forests help rural households adapt to climate variability? Evidence from Southern Malawi. World Development, 38(9):1241–1250.
- FRA (2020). Terms and Definitions. Forest Resources Assessment. Working Paper 188. Retrieved from: https://www.fao.org/3/18661EN/i8661en.pdf.
- Frelat, R., Lopez-Ridaura, S., Giller, K. E., Herrero, M., Douxchamps, S., Djurfeldt, A. A., Erenstein, O., Henderson, B., Kassie, M., Paul, B. K., et al. (2016). Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proceedings of the National Academy of Sciences*, 113(2):458–463.
- Frölich, M. and Melly, B. (2013). Unconditional quantile treatment effects under endogeneity. *Journal of Business & Economic Statistics*, 31(3):346–357.
- Fuchs, R., Pamuk, E., and Lutz, W. (2010). Education or wealth: which matters more for reducing child mortality in developing countries? *Vienna Yearbook of Population Research*, pages 175–199.
- Gallopín, G. C. (2006). Linkages between vulnerability, resilience, and adaptive capacity. *Global environmental change*, 16(3):293–303.
- Galway, L. P., Acharya, Y., and Jones, A. D. (2018). Deforestation and child diet diversity: A geospatial analysis of 15 sub-Saharan African countries. *Health & place*, 51:78–88.
- Gelo, D. and Koch, S. (2014). The Impact of Common Property Right Forestry: Evidence from Ethiopian Villages. *World Development*, 64:395–406.
- Giertz, A., Caballero, J., Galperin, D., Makoka, D., Olson, J., and German, G. (2015). Malawi agricultural sector risk assessment.World Bank, Washington, DC.
- Girard, J., Delacote, P., and Leblois, A. (2021). Agricultural households' adaptation

to weather shocks in Sub-Saharan Africa: implications for land-use change and deforestation. *Environment and Development Economics*, 26(5-6):538–560.

Global Forest Watch (2022). Retrieved from: https://globalforestwatch.org.

- Goisis, A., Remes, H., Barclay, K., Martikainen, P., and Myrskylä, M. (2017). Advanced maternal age and the risk of low birth weight and preterm delivery: a within-family analysis using Finnish population registers. *American journal of epidemiology*, 186(11):1219–1226.
- GoM (Government of Malawi) (1996). *The National Forest Policy*. Forest Department, Ministry of Natural Resources and Environmental Affairs, Lilongwe, Lilongwe.
- GoM (Government of Malawi) (2003). *Community Based Forest Management: A Supplement to the National Forest Policy of Malawi 1996*. Government of Malawi, Lilongwe.
- GoM (Government of Malawi) (2019). *Floods Post Disaster Needs Assessment Report*. Government of Malawi: Lilongwe, Malawi.
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.
- Gowela, J. and Masamba, C. (2002). State of forest and tree genetic resources in Malawi. *Food and Agriculture Organization of the United Nations: Rome, Italy.*
- Grace, K., Davenport, F., Funk, C., and Lerner, A. M. (2012). Child malnutrition and climate in Sub-Saharan Africa: An analysis of recent trends in Kenya. *Applied Geography*, 35(1-2):405–413.
- Guo, B. (2011). Household assets and food security: Evidence from the survey of program dynamics. *Journal of Family and Economic Issues*, 32:98–110.
- Gérardeaux, E., Loison, R., Palaï, O., and Sultan, B. (2018). Adaptation strategies to climate change using cotton (Gossypium hirsutum L.) ideotypes in rainfed

tropical cropping systems in Sub-Saharan africa. A modeling approach. *Field Crops Research*, 226:38–47.

- Haile, B., Signorelli, S., Azzarri, C., and Johnson, T. (2018). Welfare effects of weather variability: Multi-country evidence from Africa south of the Sahara. *PloS* one, 13(11):e0206415.
- Hajjar, R., Oldekop, J., Cronkleton, P., Newton, P., Russell, A., and Zhou, W. (2021).
 A global analysis of the social and environmental outcomes of community forests. *Nature Sustainability*, 4:216–224.
- Halstead, P. and O'Shea, J. (1982). A friend in need is a friend indeed: social storage and the origins of social ranking. *Ranking, resource and exchange*, 92:99.
- Hampel, F. R. (1974). The influence curve and its role in robust estimation. *Journal* of the american statistical association, 69(346):383–393.
- Hansen, M. and Song, X. (2018). Vegetation Continuous Fields (VCF) Yearly Global 0.05 Deg [Data set]. NASA EOSDIS Land Processes Distributed Active Archive Center.
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., et al. (2013).
 High-Resolution GlobalMaps of 21st-Century Forest Cover Change. *Science*, 342(6160):850–853.
- Harpending, H. and Davis, H. (1977). Some implications for hunter-gatherer ecology derived from the spatial structure of resources. *World Archaeology*, 8(3):275–286.
- Harris, D. (2019). Intensification benefit index: how much can rural households benefit from agricultural intensification? *Experimental Agriculture*, 55(2):273–287.

- Harris, D. and Orr, A. (2014). Is rainfed agriculture really a pathway from poverty? *Agricultural Systems*, 123:84–96.
- Hassan, R. M. and Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, 2(311-2016-5521):83–104.
- Headey, D., Hirvonen, K., Hoddinott, J., and Stifel, D. (2019). Rural Food Markets and Child Nutrition. *American Journal of Agricultural Economics*, 101(5):1311–1327.
- Hegde, R. and Bull, G. (2008). Economic shocks and miombo woodland resource use: a household level study in Mozambique. *Department of Forest Resource Management, University of British Columbia*, pages 80–105.
- Helgeson, J. F., Dietz, S., and Hochrainer-Stigler, S. (2013). Vulnerability to weather disasters: the choice of coping strategies in rural Uganda. *Ecology and Society*, 18(2).
- Hisali, E., Birungi, P., and Buyinza, F. (2011). Adaptation to climate change in Uganda: evidence from micro level data. *Global environmental change*, 21(4):1245–1261.
- Hoddinott, J., Alderman, H., Behrman, J. R., Haddad, L., and Horton, S. (2013).The economic rationale for investing in stunting reduction. *Maternal & Child Nutrition*, 9:69–82.
- Hoddinott, J. and Kinsey, B. (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and statistics*, 63(4):409–436.
- Hodgson, J. M., Hsu-Hage, B. H. H., and Wahlqvist, M. L. (1994). Food variety as a quantitative descriptor of food intake. *Ecology of food and nutrition*, 32(3-4):137–148.

- Hoffman, A. L., Kemanian, A. R., and Forest, C. E. (2018). Analysis of climate signals in the crop yield record of sub-Saharan Africa. *Global change biology*, 24(1):143–157.
- Holden, S. (2014). Agricultural household models for Malawi: Household heterogeneity, market characteristics, agricultural productivity, input subsidies, and price shocks. A baseline report. Technical report, Centre for Land Tenure Studies Working Paper.
- Holleman, C., Rembold, F., Crespo, O., and Conti, V. (2020). The impact of climate variability and extremes on agriculture and food security An analysis of the evidence and case studies. Background paper for The State of Food Security and Nutrition in the World 2018. FAO Agricultural Development Economics Technical Study No. 4. Rome, FAO.
- Hoque, M. (2012). Advanced maternal age and outcomes of pregnancy: a retrospective study from South Africa. *Biomed Res*, 23(2):281–285.
- Hulme, M., Doherty, R., Ngara, T., New, M., and Lister, D. (2001). African climate change: 1900-2100. *Climate research*, 17(2):145–168.
- Huluka, A. T. and Wondimagegnhu, B. A. (2019). Determinants of household dietary diversity in the Yayo biosphere reserve of Ethiopia: An empirical analysis using sustainable livelihood framework. *Cogent Food & Agriculture*, 5(1):1690829.
- IMF (2017). Malawi agricultural sector wide approach. A Prioritised and Harmonised Agricultural Development Agenda: 2011–2015. Lilongwe, Malawi.
- INDDEX Project (2018). *Data4Diets: building blocks for diet-related food security analysis*. Tufts University Boston, MA.
- IPCC (2022). Impacts, Adaptation, and Vulnerability. Contribution of Working Group ii to the Sixth Assessment Report of the Intergovernmental Panel on

Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. In press.

- IPCC (2023). Climate .Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 35-115.
- Jagger, P. and Perez-Heydrich, C. (2016). Land use and household energy dynamics in Malawi. *Environmental Resource Letters*, 11:125004.
- Jagger, P. and Shively, G. (2014). Land use change, fuel use and respiratory health in Uganda. *Energy policy*, 67:713–726.
- Jalan, J. and Ravallion, M. (2002). Geographic poverty traps? A micro model of consumption growth in rural China. *Journal of Applied Econometrics*, 17(4):329–346.
- James, R. and Washington, R. (2013). Changes in African temperature and precipitation associated with degrees of global warming. *Climatic change*, 117:859–872.
- Jankowska, M. M., Lopez-Carr, D., Funk, C., Husak, G. J., and Chafe, Z. A. (2012). Climate change and human health: Spatial modeling of water availability, malnutrition, and livelihoods in Mali, Africa. *Applied Geography*, 33:4–15.
- Jayne, T., Wineman, A., Chamberlin, J., Muyanga, M., and Yeboah, F. K. (2022). Changing farm size distributions and agricultural transformation in sub-Saharan Africa. *Annual Review of Resource Economics*, 14:109–130.
- Jodha, N. S. (1978). Effectiveness of farmers' adjustments to risk. *Economic and Political Weekly*, pages A38–A48.
- Johns, T., Maundu, P., et al. (2006). Forest biodiversity, nutrition and population health in market-oriented food systems. *UNASYLVA-FAO-*, 57(2):34.

- Johnson, K. B., Jacob, A., and Brown, M. E. (2013). Forest cover associated with improved child health and nutrition: evidence from the Malawi Demographic and Health Survey and satellite data. *Global Health: Science and Practice*, 1(2):237–248.
- Johnston, D., Stevano, S., Malapit, H. J., Hull, E., and Kadiyala, S. (2018). Time use as an explanation for the agri-nutrition disconnect: evidence from rural areas in low and middle-income countries. *Food policy*, 76:8–18.
- Jones, P. G. and Thornton, P. K. (2003). The potential impacts of climate change on maize production in Africa and Latin America in 2055. *Global environmental change*, 13(1):51–59.
- Jumbe, C. and Angelsen, A. (2006). Do the Poor Benefit from Devolution Policies? Evidence from Malawi's Forest Co-Management Program. *Land Economics*, 82(4):562–581.
- Kabeer, N. (1999). Resources, agency, achievements: Reflections on the measurement of women's empowerment. *Development and change*, 30(3):435–464.
- Kabeer, N. (2005). Gender equality and women's empowerment: A critical analysis of the third Millennium Development Goal. *Gender & Development*, 13(1):13–24.
- Kajembe, G. C. and Nzunda, E. F. (2002). Nguru South Catchment Forest Reserve Profile. *PEMA (Participatory Environmental Management Program)*.
- Kamoto, J. F., Missanjo, E., and Djenontin, I. N. (2023). An assessment of Participatory Forest Management inspired by adaptive collaborative management in Malawi. *Responding to Environmental Issues through Adaptive Collaborative Management*, page 195.
- Keane, A., Lund, J., and Bluwstein, J. (2020). Impact of Tanzania's Wildlife Management Areas on household wealth. *Nature Sustainability*, 3:226–233.

- Kennedy, G., Ballard, T., and Dop, M. C. (2011). Guidelines for measuring household and individual dietary diversity. Food and Agriculture Organization of the United Nations.
- Khandelwal, N., Mandliya, J., Nigam, K., Patil, V., Mathur, A., and Pathak, A. (2020). Determinants of motor, language, cognitive, and global developmental delay in children with complicated severe acute malnutrition at the time of discharge: An observational study from central india. *PLoS One*, 15(6):e0233949.
- Knight, J., Weir, S., and Woldehanna, T. (2003). The role of education in facilitating risk-taking and innovation in agriculture. *The journal of Development studies*, 39(6):1–22.
- Knox, J., Hess, T., Daccache, A., and Wheeler, T. (2012). Climate change impacts on crop productivity in Africa and South Asia. *Environmental research letters*, 7(3):034032.
- Kolstad, E. W. and Johansson, K. A. (2011). Uncertainties associated with quantifying climate change impacts on human health: a case study for diarrhea. *Environmental health perspectives*, 119(3):299–305.
- Kosmowski, F., Leblois, A., and Sultan, B. (2016). Perceptions of recent rainfall changes in Niger: a comparison between climate-sensitive and non-climate sensitive households. *Climatic change*, 135:227–241.
- Kotir, J. H. (2011). Climate change and variability in Sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. *Environment, Development and Sustainability*, 13:587–605.
- Kraay, A. and McKenzie, D. (2014). Do poverty traps exist? Assessing the evidence. *Journal of Economic Perspectives*.
- Kuruvilla, S., Bustreo, F., Kuo, T., Mishra, C., Taylor, K., Fogstad, H., Gupta, G. R., Gilmore, K., Temmerman, M., Thomas, J., et al. (2016). The Global strategy

for women's, children's and adolescents' health (2016–2030): a roadmap based on evidence and country experience. *Bulletin of the World Health Organization*, 94(5):398.

- Lade, S. J., Haider, L. J., Engström, G., and Schlüter, M. (2017). Resilience offers escape from trapped thinking on poverty alleviation. *Science Advances*, 3(5):e1603043.
- Levy, K., Smith, S. M., and Carlton, E. J. (2018). Climate change impacts on waterborne diseases: moving toward designing interventions. *Current Environmental Health Reports*, 5:272–282.
- Lewis, J. (2002). Scarcity and Abundance: Contrasting Conceptions of the Forest in Northern Congo-Brazzaville, and Issues for Conservation. In *Ninth International Conference on Hunting and Gathering Societies, Edinburgh Conference Centre, Heriot-Watt University, September*, pages 9–13.
- Libois, F., Baland, J.-M., Delbart, N., and Pattanayak, S. (2022). Community Forest Management: The story behind a success story in Nepal.
- Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., Al-Mazroa, M. A., Amann, M., Anderson, H. R., Andrews, K. G., et al. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease study 2010. *The lancet*, 380(9859):2224–2260.
- Lobell, D. B., Bänziger, M., Magorokosho, C., and Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature climate change*, 1(1):42–45.
- Lohmann, S. and Lechtenfeld, T. (2015). The effect of drought on health outcomes and health expenditures in rural vietnam. *World development*, 72:432–448.

- Lokina, R. B. and Robinson, E. J. (2008). Determinant of the effectiveness of participatory forest management in Tanzania. *European Association of Environmental and Resource Economists, Gothenburg, Sweden.*
- Lovett, J. C. (2003). *Tanzanian Forest Law. In: International Environmental Law and Policy in Africa*, page 151–180. Environment & Policy, vol 36. Springer, Dordrecht.
- Ludwig, F., van Scheltinga, C. T., Verhagen, J., Kruijt, B., van Ierland, E., Dellink, R., de Bruin, K., de Bruin, K., et al. (2007). Climate change impacts on developing countries-EU accountability.
- Lutomia, C. K., Obare, G. A., Kariuki, I. M., and Muricho, G. S. (2019). Determinants of gender differences in household food security perceptions in the Western and Eastern regions of Kenya. *Cogent Food & Agriculture*, 5(1):1694755.
- Maddison, D. (2007). *The perception of and adaptation to climate change in Africa*, volume 4308. World Bank Publications.
- Maghembe, J. A. and Seyani, J. H. (1991). *Multipurpose trees used by smallholder farmers in Malawi: results of an ethnobotanical survey*. Int. Centre for Research in Agroforestry.
- Mahonya, S., Shackleton, C. M., and Schreckenberg, K. (2019). Non-timber forest product use and market chains along a deforestation gradient in southwest Malawi. *Frontiers in Forests and Global Change*, 2:71.
- Malawi National Statistical Office (MNSO) (2012). Third Integrated Household Survey (IHS3): Basic Information Document. Zomba, Malawi. Retrieved from: https://microdata.worldbank.org/index.php/catalog/1003/ download/40803.
- Malawi National Statistical Office (MNSO) (2019). 2018 Malawi Population and Housing.

- Maleta, K. (2006). Undernutrition. *Malawi medical journal: the journal of Medical Association of Malawi*, 18(4):189.
- Mansuri, G. and Rao, V. (2013). *Localizing Development: Does Participation Work?* World Bank, Washington D.C.
- Mauambeta, D. D., Chitedze, D., Mumba, R., and Gama, S. (2010). Status of forests and tree management in Malawi. *Coord. Union Rehabil. Environ*.
- Maxwell, D., Coates, J., and Vaitla, B. (2013). How do different indicators of household food security compare? Empirical evidence from Tigray. *Feinstein International Center*, pages 1–19.
- Mazunda, J. and Shively, G. (2015). Measuring the forest and income impacts of forest user group participation under Malawi's Forest Co-management Program. *Ecological Economics*, 119:262–273.
- McCarthy, N., Kilic, T., Brubaker, J., Murray, S., and de la Fuente, A. (2021). Droughts and floods in Malawi: Impacts on crop production and the performance of sustainable land management practices under weather extremes. *Environment and Development Economics*, 26(5-6):432–449.
- McDonald, C. M., Olofin, I., Flaxman, S., Fawzi, W. W., Spiegelman, D., Caulfield,
 L. E., Black, R. E., Ezzati, M., Danaei, G., and Study, N. I. M. (2013). The effect of
 multiple anthropometric deficits on child mortality: meta-analysis of individual
 data in 10 prospective studies from developing countries. *The American journal*of clinical nutrition, 97(4):896–901.
- McGuire, J. and Popkin, B. M. (1989). Beating the zero-sum game: Women and nutrition in the Third World. Part 1. *Food Nutr Bull*, 11(4):38–63.
- McKenna, C. G., Bartels, S. A., Pablo, L. A., and Walker, M. (2019). Women's decision-making power and undernutrition in their children under age five in the Democratic Republic of the Congo: A cross-sectional study. *PloS one*, 14(12):e0226041.

- McSweeney, K. (2004). Forest product sale as natural insurance: the effects of household characteristics and the nature of shock in eastern Honduras. *Society and Natural Resources*, 17(1):39–56.
- Mendelsohn, R. and Schlesinger, M. E. (1999). Climate-response functions. *Ambio*, 28(4):362–366.
- Mertz, O., Halsnæs, K., Olesen, J. E., and Rasmussen, K. (2009). Adaptation to climate change in developing countries. *Environmental management*, 43:743–752.
- Mertz, O., Theilade, I., and Raben, K. (2005). Linkages between environment and development assistance and research in Tanzania. In *Minutes from a workshop* on participatory forest management and meetings with environmental programme staff, Research Network for Environment and Development.
- Meyer, J. (2023). How do forests contribute to food security following a weather shock? Evidence from Malawi. *World Development*, 169:106307.
- Michaelowa, K., Dimova, R., and Weber, A. (2010). Ganyu Labour in Malawi: Understanding Rural Household's Labour Supply Strategies. *SSRN Electronic Journal. Published*.
- Michler, J. D., Josephson, A., Kilic, T., and Murray, S. (2022). Privacy protection, measurement error, and the integration of remote sensing and socioeconomic survey data. *Journal of Development Economics*, 158:102927.
- Miedema, S. S., Haardörfer, R., Girard, A. W., and Yount, K. M. (2018). Women's empowerment in East Africa: Development of a cross-country comparable measure. *World Development*, 110:453–464.
- Miller, D., Rana, P., Nakamura, K., Irwin, S., Cheng, S., Ahlroth, S., and Perge, E. (2021). A global review of the impact of forest property rights interventions on poverty. *Global Environmental Change*, 66:102218.

- Millner, A. and Dietz, S. (2015). Adaptation to climate change and economic growth in developing countries. *Environment and Development Economics*, 20(3):380–406.
- Ministry of Agriculture and Food Security (2011). Malawi agricultural sector wide approach. A Prioritised and Harmonised Agricultural Development Agenda: 2011–2015. Lilongwe, Malawi.
- Mora, C., Dousset, B., Caldwell, I. R., Powell, F. E., Geronimo, R. C., Bielecki, C. R., Counsell, C. W., Dietrich, B. S., Johnston, E. T., Louis, L. V., et al. (2017). Global risk of deadly heat. *Nature Climate change*, 7(7):501–506.
- Mordecai, E. A., Ryan, S. J., Caldwell, J. M., Shah, M. M., and LaBeaud, A. D. (2020). Climate change could shift disease burden from malaria to arboviruses in Africa. *The Lancet Planetary Health*, 4(9):e416–e423.
- Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the national academy of sciences*, 104(50):19680–19685.
- Moylan, H. and Kilic, T. (2017). Malawi's Fourth Integrated Household Survey 2016-2017 & Integrated Household Panel Survey 2016.
- Msuya, S. E., Adinan, J., and Mosha, N. (2014). Intimate partner violence and empowerment among women in Tanzania: prevalence and effect on utilization of reproductive and maternal health services. DHS Working Papers No. 106. Rockville, Maryland, USA: ICF International.
- Mtika, M. M. (2001). The AIDS epidemic in Malawi and its threat to household food security. *Human organization*, 60(2):178–188.
- Mueller, V. and Gray, C. (2018). Heat and adult health in China. *Population and environment*, 40:1–26.

- Mueller, V., Sheriff, G., Dou, X., and Gray, C. (2020). Temporary migration and climate variation in eastern Africa. *World Development*, 126:104704.
- Mulungu, K. and Kilimani, N. (2023). Does forest access reduce reliance on costly shock-coping strategies? Evidence from Malawi. *Ecological Economics*, 209:107827.
- Mulungu, K. and Manning, D. T. (2023). Impact of Weather Shocks on Food Security: How Effective are Forests as Natural Insurance? *The Journal of Development Studies*, 59(11):1760–1779.
- Murendo, C., Kairezi, G., and Mazvimavi, K. (2020). Resilience capacities and household nutrition in the presence of shocks. evidence from Malawi. *World Development Perspectives*, 20:100241.
- Musengimana, G., Mukinda, F. K., Machekano, R., and Mahomed, H. (2016). Temperature variability and occurrence of diarrhoea in children under five-years-old in Cape Town metropolitan sub-districts. *International journal of environmental research and public health*, 13(9):859.
- Myers, S. S., Smith, M. R., Guth, S., Golden, C. D., Vaitla, B., Mueller, N. D., Dangour, A. D., and Huybers, P. (2017). Climate change and global food systems: potential impacts on food security and undernutrition. *Annual review of public health*, 38:259–277.
- Myers, S. S., Zanobetti, A., Kloog, I., Huybers, P., Leakey, A. D., Bloom, A. J., Carlisle, E., Dietterich, L. H., Fitzgerald, G., Hasegawa, T., et al. (2014). Increasing co2 threatens human nutrition. *Nature*, 510(7503):139–142.
- National Center for Atmospheric Research (NCAR) (n.d.). Standardized precipitation evapotranspiration index (SPEI). Retrieved from: https:// climatedataguide.ucar.edu/.
- Nelson, G. C., Rosegrant, M. W., Palazzo, A., Gray, I., Ingersoll, C., Robertson, R., Tokgoz, S., Zhu, T., Sulser, T. B., Ringler, C., et al. (2010). *Food security,*

farming, and climate change to 2050: scenarios, results, policy options, volume 172. Washington DC, USA: International Food Policy Research Institute (IFPRI).

- Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., Robinson, S., Schmid, E., Schmitz, C., Tabeau, A., and Willenbockel, D. (2013). Climate change effects on agriculture: Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences*, 111(9):3274–3279.
- Neumann, R. P. and Hirsch, E. (2000). *Commercialisation of non-timber forest products: review and analysis of research*. CIFOR.
- Newton, P., Miller, D. C., Byenkya, M. A. A., and Agrawal, A. (2016). Who are forest-dependent people? A taxo nomy to aid livelihood and land use decision-making in forested regions. *Land use policy*, 57:388–395.
- Ngigi, M., Mueller, U., and Birner, R. (2015). The Role of Livestock Portfolios and Group-Based Approaches for Building Resilience in the Face of Accelerating Climate Change: An Asset-Based Panel Data Analysis from Rural Kenya. *SSRN Electronic Journal*.
- Ngwira, S. and Watanabe, T. (2019). An analysis of the causes of deforestation in Malawi: A case of Mwazisi. *Land*, 8(3):48.
- Nnam, N. (2015). Improving maternal nutrition for better pregnancy outcomes. *Proceedings of the Nutrition Society*, 74(4):454–459.
- Noack, F., Riekhof, M.-C., and Di Falco, S. (2019). Droughts, biodiversity, and rural incomes in the tropics. *Journal of the Association of Environmental and Resource Economists*, 6(4):823–852.
- Noack, F., Wunder, S., Angelsen, A., and Börner, J. (2015). Responses to weather

and climate: a cross-section analysis of rural incomes. *World Bank Policy Research Working Paper*, (7478).

- Oldekop, J. A., Sims, K. R., Karna, B. K., Whittingham, M. J., and Agrawal, A. (2019). Reductions in deforestation and poverty from decentralized forest management in Nepal. *Nature sustainability*, 2(5):421–428.
- Olivier, R. and Mwase, W. (2012). Final Evaluation of Improved Forest Management for Sustainable Livelihoods Programme. Final report, European Union.
- Opiyo, F., Wasonga, O., Nyangito, M., Schilling, J., and Munang, R. (2015). Drought adaptation and coping strategies among the Turkana pastoralists of northern Kenya. *International Journal of Disaster Risk Science*, 6:295–309.
- Orr, A., Mwale, B., and Saiti-Chitsonga, D. (2009). Exploring seasonal poverty traps: The 'six-week window' in southern Malawi. *The Journal of Development Studies*, 45(2):227–255.
- Osbahr, H., Twyman, C., Adger, W. N., and Thomas, D. S. (2008). Effective livelihood adaptation to climate change disturbance: scale dimensions of practice in Mozambique. *Geoforum*, 39(6):1951–1964.
- Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge university press.
- Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., Clarke, L., Dahe, Q., Dasgupta, P., et al. (2014). Climate change 2014: Synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. IPCC.
- Pailler, S., Naidoo, R., Burgess, N., Freeman, O., and Fisher, B. (2015). Impacts of Community-Based Natural Resource Management on Wealth, Food Security and Child Health in Tanzania. *Plos One*, 10(7):0133252.

- Pailler, S. and Tsaneva, M. (2018). The effects of climate variability on psychological well-being in India. *World Development*, 106:15–26.
- Palmer, C., Souza, G., Laray, E., Viana, V., and Hall, A. (2020). Participatory policies and intrinsic motivation to conserve forest commons. *Nature Sustainability*, 3:620–627.
- Paranjothy, S., Broughton, H., Adappa, R., and Fone, D. (2009). Teenage pregnancy: who suffers? *Archives of disease in childhood*, 94(3):239–245.
- Park, T. (2015). Direct marketing and the structure of farm sales: An unconditional quantile regression approach. *Journal of Agricultural and Resource Economics*, pages 266–284.
- Pattanayak, S. K. and Sills, E. O. (2001). Do tropical forests provide natural insurance? the microeconomics of non-timber forest product collection in the Brazilian Amazon. *Land economics*, 77(4):595–612.
- Paumgarten, F. (2005). The role of non-timber forest products as safety-nets: a review of evidence with a focus on South Africa. *GeoJournal*, 64(3):189–197.
- Pauw, K., Thurlow, J., and Van Seventer, D. (2010). *Droughts and floods in Malawi: Assessing the economy wide effects*. International Food Policy Research Institute (IFPRI).
- Peng, J., Dadson, S., Hirpa, F., Dyer, E., Lees, T., Miralles, D. G., Vicente-Serrano,
 S. M. V.-S., and Funk, C. (2019). High resolution standardized precipitation evapotranspiration index (SPEI) dataset for Africa. *Centre for Environmental Data Analysis*, 10.
- Perez-Heydrich, C., Warren, J. L., Burgert, C. R., and Emch, M. (2013). *Guidelines* on the use of DHS GPS data. ICF International.
- Petri, W. A., Miller, M., Binder, H. J., Levine, M. M., Dillingham, R., Guerrant, R. L.,

et al. (2008). Enteric infections, diarrhea, and their impact on function and development. *The Journal of Clinical Investigation*, 118(4):1277–1290.

- Pisor, A. C. and Jones, J. H. (2021). Do people manage climate risk through longdistance relationships? *American Journal of Human Biology*, 33(4):e23525.
- Porter, M. (2016). Effects of microcredit and other loans on female empowerment in Bangladesh: The borrower's gender influences intra-household resource allocation. *Agricultural Economics*, 47(2):235–245.
- Pradhan, K. C. and Mukherjee, S. (2018). Covariate and idiosyncratic shocks and coping strategies for poor and non-poor rural households in India. *Journal of Quantitative Economics*, 16(1):101–127.
- Pratley, P. (2016). Associations between quantitative measures of women's empowerment and access to care and health status for mothers and their children: a systematic review of evidence from the developing world. *Social science & medicine*, 169:119–131.
- Qadir, U. (2015). UN Development Programme (UNDP). Human Development Report 2015-Work for Human Development. *Pakistan Development Review*, 54(3):277–278.
- Quisumbing, A. R. and Maluccio, J. A. (2003). Resources at marriage and intrahousehold allocation: Evidence from Bangladesh, Ethiopia, Indonesia, and South Africa. *Oxford Bulletin of Economics and Statistics*, 65(3):283–327.
- Randell, H., Gray, C., and Grace, K. (2020). Stunted from the start: Early life weather conditions and child undernutrition in Ethiopia. *Social Science & Medicine*, 261:113234.
- Randolph, T. F., Schelling, E., Grace, D., Nicholson, C. F., Leroy, J. L., Cole, D. C., Demment, M. W., Omore, A., Zinsstag, J., and Ruel, M. (2007). Invited Review:
 Role of livestock in human nutrition and health for poverty reduction in developing countries. *Journal of Animal Science*, 85(11):2788–2800.

- Rasolofoson, R. A., Hanauer, M. M., Pappinen, A., Fisher, B., and Ricketts, T. H. (2018). Impacts of forests on children's diet in rural areas across 27 developing countries. *Science advances*, 4(8):eaat2853.
- Rees, N. (2021). The Climate Crisis Is a Child Rights Crisis: Introducing the Children's Climate Risk Index. *UNICEF*.
- Reincke, K., Vilvert, E., Fasse, A., Graef, F., Sieber, S., and Lana, M. A. (2018). Key factors influencing food security of smallholder farmers in Tanzania and the role of cassava as a strategic crop. *Food Security*, 10:911–924.
- Remme, H., Muyambi, F., Kamato, J., and Dengua, E. (2015). Technical review of community based forest management on both customary land and forest reserves (Participatory Forest Management). Final draft report, European Union.
- Richard, S., Black, R., Gilman, R., Guerrant, R., Kang, G., Lanata, C., Mølbak, K., Rasmussen, Z., Sack, R., Valentiner-Branth, P., et al. (2012). Wasting is associated with stunting in early childhood. *The Journal of Nutrition*, 142(7):1291–1296.
- Rights and Resources Initiative (2018). At a crossroads. Consequential trends in recognition of community based forest tenure from 2002 to 2017. Washington, DC.
- Rios-Avila, F. (2020). Recentered influence functions (rifs) in Stata: RIF regression and RIF decomposition. *The Stata Journal*, 20(1):51–94.
- Robinson, B. E., Holland, M. B., and Naughton-Treves, L. (2014). Does secure land tenure save forests? a meta-analysis of the relationship between land tenure and tropical deforestation. *Global Environmental Change*, 29:281–293.
- Robinson, E., Albers, H., and Williams, J. (2005). Analyzing the impact of excluding rural people from protected forests: spatial resource degradation and rural welfare. CSAE Working Paper Series 2005-03, Centre for the Study of African Economies, University of Oxford.

- Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.
- Ruel, M. T.and Harris, J. and Cunningham, K. (2013). Diet quality in developing countries. *Diet quality*, pages 239–261.
- Rytter, M. J. H., Kolte, L., Briend, A., Friis, H., and Christensen, V. B. (2014). The immune system in children with malnutrition—a systematic review. *PloS One*, 9(8):e105017.
- Salazar-Espinoza, C., Jones, S., and Tarp, F. (2015). Weather shocks and cropland decisions in rural Mozambique. *Food Policy*, 53:9–21.
- Santoso, M. V., Kerr, R. B., Hoddinott, J., Garigipati, P., Olmos, S., and Young, S. L. (2019). Role of women's empowerment in child nutrition outcomes: A systematic review. *Advances in Nutrition*, 10(6):1138–1151.
- Sant'Anna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of econometrics*, 219(1):101–122.
- Sarr, M., Ayele, M. B., Kimani, M. E., and Ruhinduka, R. (2021). Who benefits from climate-friendly agriculture? The marginal returns to a rainfed system of rice intensification in Tanzania. *World Development*, 138:105160.
- Schauberger, B., Archontoulis, S., Arneth, A., Balkovic, J., Ciais, P., Deryng, D., Elliott, J., Folberth, C., Khabarov, N., Müller, C., et al. (2017). Consistent negative response of us crops to high temperatures in observations and crop models. *Nature Communications*, 8(1):13931.
- Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

- Schoenbuchner, S. M., Dolan, C., Mwangome, M., Hall, A., Richard, S. A., Wells, J. C., Khara, T., Sonko, B., Prentice, A. M., and Moore, S. E. (2019). The relationship between wasting and stunting: a retrospective cohort analysis of longitudinal data in Gambian children from 1976 to 2016. *The American Journal of Clinical Nutrition*, 110(2):498–507.
- Schofield, C. and Ashworth, A. (1996). Why have mortality rates for severe malnutrition remained so high? *Bulletin of the World Health Organization*, 74(2):223.
- Senganimalunje, T., Chirwa, P., and Babalola, F. (2015). Potential of institutional arrangements for sustainable management of forests under co-management with local forest organisations in Mua-Livulezi Forest Reserve, Mtakataka, Malawi. *International Forestry Review*, 17(3):340–354.
- Senganimalunje, T., Chirwa, P. W., Babalola, F. D., and Graham, M. A. (2016). Does participatory forest management program lead to efficient forest resource use and improved rural livelihoods? Experiences from Mua-Livulezi Forest Reserve, Malawi. *Agroforestry systems*, 90:691–710.
- Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M., and Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. *Regional Environmental Change*, 17:1585–1600.
- Shackleton, C. M., Shackleton, S. E., and Cousins, B. (2001). The role of land-based strategies in rural livelihoods: the contribution of arable production, animal husbandry and natural resource harvesting in communal areas in South Africa. *Development Southern Africa*, 18(5):581–604.
- Sharaunga, S., Mudhara, M., and Bogale, A. (2016). Effects of 'women empowerment'on household food security in rural Kwazulu-Natal province. *Development policy review*, 34(2):223–252.

- Sheffield, J., Goteti, G., and Wood, E. F. (2006). Development of a 50-year highresolution global dataset of meteorological forcings for land surface modeling. *Journal of climate*, 19(13):3088–3111.
- Shyamsundar, P., Ahlroth, S., Kristjamiscn, P., and Onder, S. (2020). Supporting pathways to prosperity in forest landscapes A PRIME framework. *World Development*, 125:104622.
- Silvestri, S., Bryan, E., Ringler, C., Herrero, M., and Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, 12:791–802.
- Smit, B. and Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global environmental change*, 16(3):282–292.
- Smith, L. C. and Haddad, L. J. (1999). Explaining Child Malnutrition in Developing Countries. FCND Discussion Papers No. 60.
- Smith, M. R. and Myers, S. S. (2018). Impact of anthropogenic co2 emissions on global human nutrition. *Nature Climate Change*, 8(9):834–839.
- Smith, T. G. (2014). Feeding unrest: Disentangling the causal relationship between food price shocks and sociopolitical conflict in urban Africa. *Journal of Peace Research*, 51(6):679–695.
- Smucker, T. A. and Wisner, B. (2008). Changing household responses to drought in Tharaka, Kenya: vulnerability, persistence and challenge. *Disasters*, 32(2):190–215.
- Snyder, P., Delire, C., and Foley, J. (2004). Evaluating the influence of different vegetation biomes on the global climate. *Climate Dynamics*, 23:279–302.
- Ssewamala, F. M. (2004). Expanding women's opportunities: the potential of heifer projects in sub-Saharan Africa. *Development in Practice*, 14(4):550–559.

- Stern, N. H. (2007). *The Economics of Climate Change: The Stern Review*. Cambridge University Press.
- Swindale, A. and Bilinsky, P. (2006). Household dietary diversity score (HDDS) for measurement of household food access: indicator guide. *Food and Nutrition Technical Assistance Project, Academy for Educational Development.*
- Tadesse, M., Teklie, H., Yazew, G., and Gebreselassie, T. (2013). Women's empowerment as a determinant of contraceptive use in Ethiopia further analysis of the 2011 Ethiopia demographic and health survey. *DHS Further Analysis Reports*, 82.
- Tesfaye, K., Gbegbelegbe, S., Cairns, J. E., Shiferaw, B., Prasanna, B. M., Sonder, K., Boote, K., Makumbi, D., and Robertson, R. (2015). Maize systems under climate change in sub-Saharan Africa: Potential impacts on production and food security. *International Journal of Climate Change Strategies and Management*, 7(3):247–271.
- Thiede, B. C. and Strube, J. (2020). Climate variability and child nutrition: Findings from sub-Saharan Africa. *Global Environmental Change*, 65:102192.
- Thomas, D. S., Twyman, C., Osbahr, H., and Hewitson, B. (2007). Adaptation to climate change and variability: farmer responses to intra-seasonal precipitation trends in South Africa. *Climatic change*, 83(3):301–322.
- Thompson, H. E., Berrang-Ford, L., and Ford, J. D. (2010). Climate change and food security in sub-Saharan Africa: a systematic literature review. *Sustainability*, 2(8):2719–2733.
- Thorne-Lyman, A. L., Valpiani, N., Sun, K., Semba, R. D., Klotz, C. L., Kraemer, K., Akhter, N., de Pee, S., Moench-Pfanner, R., Sari, M., and Bloem, M. W. (2010).
 Household Dietary Diversity and Food Expenditures Are Closely Linked in Rural Bangladesh, Increasing the Risk of Malnutrition Due to the Financial Crisis. *The Journal of Nutrition*, 140(1):182S–188S.
- Thornton, P. K., Ericksen, P. J., Herrero, M., and Challinor, A. J. (2014). Climate variability and vulnerability to climate change: a review. *Global Change Biology*, 20(11):3313–3328.
- Tibesigwa, B., Visser, M., Collinson, M., and Twine, W. (2016). Investigating the sensitivity of household food security to agriculture-related shocks and the implication of social and natural capital. *Sustainability Science*, 11:193–214.
- Tirado, M., Hunnes, D., Cohen, M., and Lartey, A. (2015). Climate change and nutrition in Africa. *Journal of Hunger & Environmental Nutrition*, 10(1):22–46.
- Tobin, D., Jones, K., and Thiede, B. C. (2019). Does crop diversity at the village level influence child nutrition security? evidence from 11 sub-Saharan African countries. *Population and Environment*, 41:74–97.
- Tsiboe, F., Zereyesus, Y. A., Popp, J. S., and Osei, E. (2018). The effect of women's empowerment in agriculture on household nutrition and food poverty in Northern Ghana. *Social Indicators Research*, 138:89–108.
- Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., et al. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the national academy of sciences*, 100(14):8074–8079.
- UN DESA (2016). Climate change resilience: an opportunity for reducing inequalities. United Nations, New York.
- UNICEF (2011). Gender Influences on Child Survival, Health and Nutrition : A Narrative review. *New York*.
- UNICEF (2016). Multi-sectoral approaches to nutrition: nutrition-specific and nutrition-sensitive interventions to accelerate progress.

United Nations (2015). The Millennium Development Goals Report.

- USAID (n.d.). Agriculture and Food Security: Malawi. Retrieved from: https: //www.usaid.gov/malawi/agriculture-and-food-security.
- Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate*, 23(7):1696–1718.
- Villanueva, M. (2022). The Impact of Climate shocks and Women's Empowerment on child Undernutrition in Mozambique.
- Vis, H. L., Yourassowsky, C., and Van der Borght, H. (1975). A nutritional survey in the Republic of Rwanda. Brussells: Musée Royal de l'Afrique Centrale. Tervaren, Belgique. Annales-Serie In-8, Sciences Humaines., (87).
- Walelign, S., Charlery, L., and Pouliot, M. (2021). Poverty Trap or means to Escape Poverty? Empirical Evidence on the Role of Environmental Income in Rural Nepal. *The Journal of Development Studies*, 57(10):1613–1639.
- Warnatzsch, E. A. and Reay, D. S. (2019). Temperature and precipitation change in Malawi: Evaluation of CORDEX-Africa climate simulations for climate change impact assessments and adaptation planning. *Science of the Total Environment*, 654:378–392.
- Wheeler, T. and Von Braun, J. (2013). Climate change impacts on global food security. *Science*, 341(6145):508–513.
- Whiteside, M. (2000). Ganyu labour in malawi and its implications for livelihood security interventions: An analysis of recent literature and implications for poverty alleviation. *Agricultural Research and Extension Network Paper*, 99:1–10.
- Wiesmann, D., Bassett, L., Benson, T., and Hoddinott, J. (2009). Validation of the World Food Programme's Food Consumption Score and alternative indicators of household food security. Intl Food Policy Res Inst.

- World Bank (2016). Republic of Malawi: poverty assessment. Poverty and Equity Global Practice Africa Region Report, Washington, DC: World Bank Group.
- World Bank (2019). Living Standards Measurement Study: Integrated Surveys
 on Agriculture (LSMS-ISA). Retrieved from: https://www.worldbank.org/en/
 programs/lsms/initiatives/lsms-ISA.
- World Food Programme (2008). Food consumption analysis: calculation and use of the food consumption score in food security analysis. WFP: Rome, Italy.
- World Food Programme (WFP) (2008). Food consumption analysis: calculation and use of the food consumption score in food security analysis. WFP, Rome.
- World Health Organization (2006). WHO child growth standards: length/heightfor-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: methods and development.
- World Health Organization (2021). WHO malnutrition fact sheets. Retrieved from: https://www.who.int/news-room/fact-sheets/detail/malnutrition.
- Wrottesley, S., Lamper, C., and Pisa, P. (2016). Review of the importance of nutrition during the first 1000 days: maternal nutritional status and its associations with fetal growth and birth, neonatal and infant outcomes among African women. *Journal of developmental origins of health and disease*, 7(2):144–162.
- Wunder, S. (2001). Poverty alleviation and tropical forests—what scope for synergies? *World development*, 29(11):1817–1833.
- Wunder, S., Angelsen, A., and Belcher, B. (2014a). Forests, Livelihoods, and Conservation: Broadening the Empirical Base. *World Development*, 64:1–11.
- Wunder, S., Börner, J., Shively, G., and Wyman, M. (2014b). Safety nets, gap filling and forests: a global-comparative perspective. *World development*, 64:S29–S42.

- Xu, Z., Etzel, R. A., Su, H., Huang, C., Guo, Y., and Tong, S. (2012). Impact of ambient temperature on children's health: a systematic review. *Environmental research*, 117:120–131.
- Xu, Z., Huang, C., Turner, L. R., Su, H., Qiao, Z., and Tong, S. (2013). Is diurnal temperature range a risk factor for childhood diarrhea? *PLoS One*, 8(5):e64713.
- Xu, Z., Liu, Y., Ma, Z., Toloo, G., Hu, W., and Tong, S. (2014). Assessment of the temperature effect on childhood diarrhea using satellite imagery. *Scientific Reports*, 4(1):5389.
- Yisak, H., Gobena, T., and Mesfin, F. (2015). Prevalence and risk factors for under nutrition among children under five at Haramaya district, Eastern Ethiopia. *BMC pediatrics*, 15:1–7.
- Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy* of sciences, 114(35):9326–9331.
- Zhou, X., Zhou, Y., Chen, R., Ma, W., Deng, H., and Kan, H. (2013). High temperature as a risk factor for infectious diarrhea in Shanghai, China. *Journal of Epidemiology*, 23(6):418–423.
- Zivin, J. G. and Shrader, J. (2016). Temperature extremes, health, and human capital. *The Future of Children*, pages 31–50.
- Zulu, L. (2013). Bringing people back into protected forests in developing countries: Insights from co-management in Malawi. *Sustainability*, 5(5):1917–1943.
- Zwane, A. (2007). Does poverty constrain deforestation? Econometric evidence from Peru. *Journal of Development Economics*, 84(1):330–349.

Appendices

Appendix A

Appendix for Chapter 1

A.1 LSMS-ISA household tracking process

Following the first round of the Integrated Household Survey (HIS) Program that took place between March 2010 and March 2011 via the Third Integrated Household Survey (ISH3), all households that had been interviewed were tracked and when possible, re-interviewed during the following rounds of the survey in 2013 and 2016/2017. Split-off households and individuals, who moved away from their initial location (that of 2010/2011) to establish and/or join new households were also tracked and interviewed from one round to the next, allowing to expand the panel sample each survey wave. In the analysis we keep both original and split-off households, constituting a final sample of 2,508 households. The LSMS-ISA recently provided assistance of technical and financial nature for a fifth Integrated Household Survey (IHS5) for the period 2019/2020 that is not included in this work.

A.2 Nutritional value weights of the FCS

Table A.2.1: Nutritional value weights per food group

Food Groups	Weights
1) Main staples	
Cereals, Grains and Cereal Products	2
Roots, Tubers, and Plantains	
2) Nuts and Pulses	3
3) Vegetables	1
4) Fruits	1
5) Meat, Fish and Animal Products	4
6) Milk/Milk Products	4
7) Sugars/Sugar Products/Honey	0.5
8) Fats/Oils	0.5

Notes: The food groups, and their assigned weights, are derived from the (World Food Programme, 2008).

A.3 Food items in each food group

Table A.3.1: Food items detail

Main Staples

Cereals, Grains and Cereal Products

Maize Grain/Flour; Green Maize; Rice; Finger Millet; Pearl Millet,Sorghum, Wheat Flour; Bread; Pasta; Other Cereal

Roots, Tubers, and Plantains Cassava Tuber/Flour; Sweet Potato; Irish Potato; Other Tuber/Plantain

Nuts and Pulses

Bean; Pigeon Pea; Macademia Nut; Groundnut; Ground Bean; Cow Pea; Other Nut/Pulse

Vegetables

Onion; Cabbage; Tanaposi; Nkhwani; Wild Green Leaves; Tomato; Cucumber; Other Vegetables/Leaves

Fruits

Mango; Banana; Citrus; Pineapple; Papaya; Guava; Avocado; Apple; Other Fruit

Meat, Fish and Animal Products

Egg; Dried/Fresh/Smoked Fish (Excluding Fish Sauce/Powder); Beef; Goat Meat; Pork; Poultry; Other Meat

Milk/Milk Products

Fresh/Powdered/Soured Milk; Yogurt; Cheese; Other Milk Product - Excluding Margarine/Butter or Small Amounts of Milk for Tea/Coffee

Sugars/Sugar Products/Honey

Sugar; Sugar Cane; Honey; Jam; Jelly; Sweets/Candy/Chocolate; Other Sugar Product

Fats/Oils

Cooking Oil; Butter; Margarine; Other Fat/Oil

Notes: The food items in each food group are based on the food items listed in the World Bank's LSMS-ISA data for Malawi.

A.4 Classification of the Food Consumption Score (FCS)



Figure A.4.1: FCS categories

Notes:These graphs represent the classification of households, per survey round, based on their FCS statuses. Data derived from the LSMS-ISA for Malawi.

A.5 Frequency of consumption per food group



Figure A.5.1: Consumption frequency per FCS food group

Notes:This graph represents the average frequencies of consumption (unweighted) for each food group that makes up the FCS, and per survey round. It was constructed using data from the LSMS-ISA for Malawi.

A.6 Summary statistics

Table A.6.1: Summary statistic	cs of the variables	used in the analysi	is
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	2010		2013		20	16
Variables	Mean	Sd.	Mean	Sd.	Mean	Sd.
Household characteristics						
Food Consumption Score (FCS)	51.228	19.418	53.322	18.958	47.103	19.794
Unweighted Food Consumption Score (unweighted FCS)	30.220	9.971	31.537	9.601	28.822	10.161
Food Variety Score (FVS)	21.730	8.959	24.782	10.622	21.116	9.634
Household size (HH size)	5.238	2.353	5.429	2.455	4.891	2.287
Owns Livestock $(1 = yes)$	0.457	0.498	0.486	0.499	0.478	0.500
Durable asset value (log, real value, MWK*)	8.886	1.910	9.300	1.899	9.017	1.917
Food expenditures (Log, real value, MWK)	7.128	1.236	7.558	1.128	7.528	1.063
Number of durable goods	4.811	3.794	5.049	4.149	4.409	3.923
Participates in <i>ganyu</i> labor (1= Yes)	0.356	0.479	0.419	0.493	0.616	0.486
Distance to nearest population center (km)	26.758	19.133	27.738	19.516	27.531	19.535
Distance to nearest lake (km)	55.953	33.973	55.648	34.393	55.399	34.846
Forest and weather shock variables						
Forest $cover_{t-1}$ (%)	13.764	7.838	13.121	7.427	12.649	7.964
Moderate weather shock _{$t-1$} (1= yes)	0.322	0.467	0.430	0.495	0.139	0.346
Severe weather $shock_{t-1}$ (1= yes)	0	0	0.327	0.469	0.059	0.236

Notes: *The local currency in Malawi, the Malawian Kwacha.

A.7 Average marginal effects





Notes: The plot on the left displays the average marginal effects of a moderate weather shock on the predicted mean of the FCS, while accounting for the values of the forest cover variable. The right plot, on the other hand, considers the effects of a severe weather shock.

A.8 Alternative food security indicators

Dependent variables	Unweight	ed FCS $_{i,v,t}$	$\mathrm{FVS}_{i,v,t}$		
Shock severity	Moderate	Severe	Moderate	Severe	
Variables	(1)	(2)	(3)	(4)	
Shock _{$v,t-1$} (ref: no shock)	-2.262***	-2.659***	-2.227***	-1.109	
	(0.581)	(0.624)	(0.813)	(0.773)	
$Forest_{v,t-1}$	-0.089***	-0.068***	-0.080***	-0.070**	
	(0.023)	(0.022)	(0.028)	(0.028)	
$\mathbf{Shock}_{v,t-1} \ \mathbf{X} \ \mathbf{Forest}_{v,t-1}$	0.182***	0.191***	0.153***	0.139***	
	(0.038)	(0.037)	(0.046)	(0.039)	
Control variables	\checkmark	\checkmark	\checkmark	\checkmark	
Household Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark	
Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark	
Nb. of households	2283	2283	2283	2283	
Observations	6,432	6,432	6,432	6,432	
R-squared	0.762	0.734	0.761	0.733	

Table A.8.1: Unweighted FCS and FVS

Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). The dependent variable corresponds to the unweighted Food Consumption Score (unweighted $FCS_{i,v,t}$) in columns 1 & 2; and to the Food Variety Score ($FVS_{i,v,t}$) in columns 3 & 4. Additionally, the weather shock variable (Shock_{v,t-1}) corresponds to a moderate weather shock (SPEI index equals or exceeds 1 in absolute value) in columns 1 & 3, and to a severe weather shock (SPEI index equals or exceeds 1.5 in absolute value) in columns 2 & 4.

A.9 Alternative food security indicators (Cont.)

Dependent variable Variables	Unweighted $FCS_{i,v,t}$ (1)	FVS $_{i,v,t}$ (2)
Dry shock _{<i>v</i>,<i>t</i>-1} (ref: no shock)	-1.938***	-2.555**
·)·	(0.704)	(1.088)
$\operatorname{Forest}_{v,t-1}$	-0.068***	-0.077**
	(0.023)	(0.030)
Dry $\mathbf{shock}_{v,t-1}$ 1 X $\mathbf{Forest}_{v}, t-1$	0.197***	0.180***
	(0.044)	(0.059)
Wet $shock_{v,t-1}$ (ref: no shock)	-2.470***	-1.563*
	(0.635)	(0.879)
Wet $shock_{v,t-1}$ 1 X Forest $_{v,t-1}$	0.095**	0.081
	(0.047)	(0.063)
Control variables	\checkmark	\checkmark
Household Fixed Effects	\checkmark	\checkmark
Year Fixed Effects	\checkmark	\checkmark
Nb. of households	2283	2283
Observations	6,432	6,432
R-squared	0.763	0.734

Table A.9.1: Differences between dry and wet shocks - alternative measures

Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). A dry shock corresponds to SPEI values less than or equal to -1. A wet shock corresponds to SPEI values equal or greater than 1. The dependent variable is the unweighted FCS in column 1, and the FVS in column 2.

A.10 Summary statistics according to quartiles

Ganyu (1=yes)												
Quartile	Ν	Mean	Min	Max	Sd.							
1	1705	0.605	0	1	0.489							
2	1700	0.526	0	1	0.499							
3	1696	0.441	0	1	0.497							
4	1700	0.2	0	1	0.400							
	Lives	stock (l=ye	s)								
Quartile	Ν	Mean	Min	Max	Sd.							
1	1705	0.444	0	1	0.497							
2	1700	0.515	0	1	0.500							
3	1696	0.583	0	1	0.493							
4	1700	0.415	0	1	0.493							

Table A.10.1: Livestock ownership & ganyu labor by quartile

A.11 Forests as a safety net by asset quartile

Moderate shock Severe shock										
Dependent variable: Food Consumption Score $(FCS_{i,v,t})$										
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
Shock _{$v,t-1$} (ref: no shock)	-1.616	-5.276	-1.730	-4.044	-1.290	-11.678**	-4.269	-0.713		
	(3.022)	(3.425)	(3.753)	(2.914)	(3.162)	(5.231)	(3.880)	(3.090)		
$Forest_{v,t-1}$	-0.074	-0.154	-0.092	-0.076	-0.076	-0.113	-0.065	-0.056		
	(0.144)	(0.136)	(0.132)	(0.123)	(0.120)	(0.134)	(0.130)	(0.128)		
$\mathbf{Shock}_{v,t-1} \ \mathbf{X} \ \mathbf{Forest}_{v,t-1}$	0.034	0.302	0.179	0.443***	0.056	0.546*	0.221	0.305**		
	(0.160)	(0.235)	(0.222)	(0.126)	(0.174)	(0.327)	(0.222)	(0.133)		
Control variables	\checkmark									
Household Fixed Effects	\checkmark									
Year Fixed Effects	\checkmark									
Nb. of households	419	377	409	503	419	377	409	503		
Observations	944	806	889	1,267	944	806	889	1,267		
R-squared	0.657	0.666	0.674	0.632	0.656	0.670	0.675	0.631		

Table A.11.1: Forests as a safety net by asset quartile (moderate & severe shock)

Standard errors in parentheses clustered at the EA level.

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

Notes: The estimator is a linear model with high dimensional fixed effects (Correia, 2017). The weather shock variable (Shock_{v,t-1}) corresponds to a moderate weather shock (SPEI index equals or exceeds 1 in absolute value) in columns 1 to 4. In columns 5 to 8, the weather shock variable corresponds to a severe weather shock (SPEI index equals or exceeds 1.5 in absolute value). The sample is divided into quartiles based on the value of durable goods owned by households (expressed in log, and in MWK).

Appendix **B**

Appendix for Chapter 2

B.1 Trends



Figure B.1.1: Trends for the Food Consumption Score (FCS)



Figure B.1.2: Trends for the value of assets and non-food expenditures



Figure B.1.3: Trends for gross forest loss (%) (restricted and full sample)

B.2 Covariate balancing tests

	Unmatched (U)	Me	Mean			t-test	
	Matched (M)	Treated	Control	%	t	p > t	
Variables						1 11	
Household size	U	5.4545	5.3953	2.5	0.30	0.764	
	Μ	5.4545	5.37	3.5	0.33	0.744	
Livestock ownership (1=yes)	U	0.59659	0.46382	26.8	3.19	0.001	
	Μ	0.59659	0.59554	0.2	0.02	0.984	
Asset value (log, real terms, MWK)	U	8.4857	9.0824	-33.7	-3.90	0.000	
	Μ	8.4857	8.3212	9.3	0.93	0.351	
Food expenditures (log, real terms, MWK)	U	6.9076	7.3299	-40.7	-4.36	0.000	
1	Μ	6.9076	6.7546	14.7	1.46	0.145	
Distance to pop. center (km)	U	32.39	26.015	34.3	4.02	0.000	
	Μ	32.39	33.836	-7.8	-0.72	0.470	
Forest cover (%) - 10 km buffer	U	16.42	12.962	54.1	5.57	0.000	
	Μ	16.42	16.142	4.3	0.37	0.711	
Elevation (m)	U	896.05	1000.2	-30.4	-4.52	0.000	
	М	896.05	949.25	-15.5	-1.40	0.163	

	Table B.2.1:	Balancing	test -	Non-food	expenditures,	2016
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Notes: The outcome for which these covariates are matched is non-food expenditures (log) in the past week. The number of untreated and treated households is of 774 and 176 respectively after matching.

	Unmatched (U)	Unmatched (U) Mean		Bias	t-t	est
	Matched (M)	Treated	Control	%	t	p> t
Variables						
Household size	U	5.5687	5.4786	3.9	0.51	0.611
	Μ	5.5687	5.346	9.5	0.99	0.323
Livestock ownership (1=yes)	U	0.61611	0.45726	32.2	4.20	0.000
	Μ	0.61611	0.6123	0.8	0.08	0.936
Asset value (log, real terms, MWK)	U	8.4148	9.0374	-35.0	-4.45	0.000
	Μ	8.4148	8.2687	8.2	0.90	0.367
Food expenditures (log, real terms, MWK)	U	6.8618	7.3345	-45.8	-5.42	0.000
	М	6.8618	6.7232	13.4	1.44	0.151
Distance to pop. center (km)	U	32.488	26.376	32.5	4.17	0.000
	Μ	32.488	34.478	-10.6	-1.06	0.290
Forest cover (%) - 10 km buffer	U	16.668	12.69	63.4	7.22	0.000
	Μ	16.668	16.373	4.7	0.43	0.671
Elevation (m)	U	896.96	996.88	-29.9	-4.85	0.000
	М	896.96	938.43	-12.4	-1.22	0.223

Table B.2.2: Balancing test - Non-food expenditures, 2019

Notes: The outcome for which these covariates are matched is non-food expenditures (log) in the past week. The number of untreated and treated households is of 936 and 211 respectively after matching.

Unweighted DiD results B.3

2016					2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment	-2.493	-0.867***	-0.667**	0.000755	-1.773	-0.777***	-0.713***	-0.000993	
	(3.126)	(0.282)	(0.271)	(0.0264)	(3.050)	(0.273)	(0.248)	(0.0282)	
Post treatment	-1.884*	0.0416	0.00672	0.0711*	-0.461	0.108	-0.0293	0.0679**	
	(1.103)	(0.108)	(0.0966)	(0.0407)	(1.250)	(0.0844)	(0.107)	(0.0326)	
Treatment X Post treatment	-7.878***	-0.114	-0.817***	0.0458	-2.623	-0.0160	0.223	0.0563	
	(2.484)	(0.166)	(0.234)	(0.0642)	(1.959)	(0.241)	(0.287)	(0.0641)	
Observations	2,572	2,330	2,333	1,508	2,834	2,488	2,533	1,800	
R-squared	0.028	0.032	0.054	0.048	0.005	0.025	0.017	0.049	

Table B.3.1: DiD results with no matching weights

Standard errors in parentheses clustered at the EA level. *** p < 0.01, ** p < 0.05, * p < 0.1. *Notes*: Unweighted DiD estimation.

B.4 Additional matching variables

	2016						2019			
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
Treatment	2.826	0.115	0.0333	-0.0557	0.721	-0.398	-0.150	-0.117		
	(3.318)	(0.314)	(0.273)	(0.0603)	(3.747)	(0.319)	(0.283)	(0.0863)		
Post treatment	-3.474	0.524***	-0.168	0.0934	-0.643	0.374	-0.0655	0.157**		
	(2.308)	(0.190)	(0.265)	(0.0627)	(2.308)	(0.235)	(0.283)	(0.0764)		
Treatment X Post treatment	-8.170**	-0.549**	-0.722*	-0.0101	-3.293	-0.290	-0.0292	-0.0669		
	(3.666)	(0.234)	(0.376)	(0.0753)	(2.705)	(0.353)	(0.441)	(0.0900)		
Observations	1,286	1,244	1,137	936	1,604	1,529	1,322	1,032		
R-squared	0.070	0.013	0.049	0.076	0.008	0.028	0.003	0.133		

Table B.4.1: Main results with additional matching variables

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pp. (km), daily market in the community (1=yes), permanent ADMARC (Agricultural Development and Marketing Corporation) market in the community (1=yes), place in the community to purchase common medicines such as pain killers (1=yes), health clinic (Chipatala) in the community (1=yes), post office in the community (1=yes), irrigation scheme in the community (1=yes), community owns a communal forest (1=yes), % under agriculture within \sim 1 km buffer, forest cover (%) - 10 km buffer, elevation (m).

B.5 Removal of Lilongwe district

		20)16		2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment	5.327*	0.000210	0.178	0.0156	6.311**	0.146	0.113	0.0148	
	(2.762)	(0.249)	(0.245)	(0.0181)	(2.704)	(0.233)	(0.217)	(0.0203)	
Post treatment	-3.010	0.380***	-0.0299	0.140*	1.268	0.476***	-9.18e-05	0.126**	
	(1.938)	(0.138)	(0.192)	(0.0766)	(1.419)	(0.118)	(0.212)	(0.0596)	
Treatment X Post treatment	-7.429**	-0.319	-0.804**	-0.0223	-5.558***	-0.375	0.0697	0.00992	
	(3.226)	(0.199)	(0.305)	(0.0924)	(1.846)	(0.248)	(0.359)	(0.0809)	
Observations	1,326	1,279	1,137	952	1,562	1,476	1,318	1,099	
R-squared	0.058	0.008	0.040	0.096	0.022	0.010	0.002	0.138	

Table B.5.1: Main results without Lilongwe district

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Both Lilongwe and Lilongwe non-city are removed. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

B.6 Heterogeneity-robust estimator

		20	16		2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment effect	-12.872***	-1.037**	-0.976**	0.003	-6.498**	-0.790**	-1.012***	-0.009	
	(3.605)	(0.423)	(0.398)	(0.075)	(3.113)	(0.366)	(0.353)	(0.058)	
Observations	1218	1006	1009	757	1485	1180	1203	651	
Switchers	45	37	37	3	68	55	59	2	

Table B.6.1: Heterogeneity-robust estimator - no covariates

Standard errors in parentheses clustered at the EA level.

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

Notes: Heterogeneity-robust estimator (De Chaisemartin and D'Haultfœuille, 2020). No covariates.

Table B.6.2: Main results using heterogeneity-robust estimator with cova	iriates
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		20)16		2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment effect	-12.984***	-1.031**	-0.959***	-0.0001	-6.645***	-0.787**	-1.074***	0.039	
	(4.228)	(0.419)	(0.350)	(0.080)	(2.510)	(0.393)	(0.321)	(0.041)	
Observations	1063	1003	897	631	1292	1176	1067	532	
Switchers	41	37	33	3	63	55	55	1	

Standard errors in parentheses clustered at the EA level.

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

Notes: Heterogeneity-robust estimator (De Chaisemartin and D'Haultfœuille, 2020). Control variables (using values at baseline): household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

B.7 Treatment effect - 2013 sample

		Baseline	matching	5		Extended	matchin	g
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	4.490*	0.0674	-0.213	0.000524	2.434	0.162	0.0133	-0.0418
	(2.404)	(0.187)	(0.208)	(0.0222)	(2.910)	(0.244)	(0.234)	(0.0520)
Post treatment	3.667***	0.653***	-0.0632	0.0866**	3.583**	0.859***	0.231	0.0506
	(1.332)	(0.121)	(0.152)	(0.0340)	(1.585)	(0.220)	(0.184)	(0.0621)
Treatment X Post treatment	-3.624**	-0.287	0.224	-0.0653	-3.522	-0.508*	-0.0915	-0.0309
	(1.787)	(0.185)	(0.247)	(0.0394)	(2.115)	(0.286)	(0.270)	(0.0631)
Observations	1,412	1,338	1,225	1,008	1,022	973	924	738
R-squared	0.013	0.026	0.003	0.061	0.007	0.036	0.004	0.059

Table B.7.1: Treatment effect on policy outcomes (2013 sample)

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. The post period considered in these estimations is 2013, with 2010 as the baseline year. Matching variables for columns 1-4: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m). Matching variables for columns 5-8: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), daily market in the community (1=yes), permanent ADMARC (Agricultural Development and Marketing Corporation) market in the community (1=yes), place in the community to purchase common medicines such as pain killers (1=yes), health clinic (Chipatala) in the community (1=yes), post office in the community (1=yes), irrigation scheme in the community (1=yes), community owns a communal forest (1=yes), % under agriculture within ~ 1 km buffer, forest cover (%) - 10 km buffer, elevation (m).

B.8 Doubly-robust estimator

	2016				2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment effect	-8.229*** (2.845)	-0.402*** (0.149)	-0.598 (0.401)	0.025 (0.066)	-5.105*** (1.290)	-0.454*** (0.174)	0.142 (0.270)	-0.007 (0.055)	
Observations	2,044	1,932	1,728	1,256	2,458	2,242	0.270	1,490	

Table B.8.1: Main results using doubly-robust estimator

Standard errors in parentheses clustered at the EA level.

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

Notes: Improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (Sant'Anna and Zhao, 2020). Covariates: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

B.9 Additional buffers

	15 km								
		20	016		2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment	2.841	0.108	-0.0164	0.00263	4.966*	0.0507	-0.0517	-0.00161	
	(3.068)	(0.316)	(0.252)	(0.0251)	(2.848)	(0.266)	(0.218)	(0.0283)	
Post treatment	-2.373	0.479***	-0.208	0.132	1.377	0.346***	-0.0250	0.111**	
	(1.798)	(0.155)	(0.191)	(0.0947)	(1.112)	(0.108)	(0.186)	(0.0483)	
Treatment X Post	-7.535**	-0.470**	-0.790**	0.00478	-6.009***	-0.501**	-0.0307	0.0640	
	(3.206)	(0.229)	(0.343)	(0.113)	(1.358)	(0.237)	(0.376)	(0.0774)	
Observations	1,186	1,149	1,064	762	1,372	1,298	1,226	914	
R-squared	0.045	0.010	0.059	0.084	0.015	0.009	0.001	0.122	

Table B.9.1: Treatment effect on policy outcomes (15 km buffer)

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

	25 km								
		20	016		2019				
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Treatment	3.673	0.0324	-0.0717	-0.0302	4.673*	0.0218	-0.0840	-0.0103	
	(2.608)	(0.237)	(0.228)	(0.0327)	(2.739)	(0.236)	(0.208)	(0.0313)	
Post treatment	-2.403	0.405***	-0.195	0.0931	1.628	0.519***	0.0261	0.129**	
	(1.525)	(0.110)	(0.164)	(0.0775)	(1.404)	(0.121)	(0.157)	(0.0542)	
Treatment X Post	-6.800**	-0.366**	-0.644**	0.0162	-5.156***	-0.409*	-0.0572	-0.00690	
	(3.127)	(0.175)	(0.269)	(0.0913)	(1.930)	(0.243)	(0.321)	(0.0748)	
Observations	1,920	1,865	1,761	1,180	2,362	2,257	2,114	1,349	
R-squared	0.038	0.009	0.045	0.056	0.011	0.015	0.001	0.082	

Table B.9.2: Treatment effect on policy outcomes (25 km buffer)

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

B.10 Households treated in Phase I

			5 k	m		
		2016			2019	
Dependent variables	FCS	Assets	Exp.	FCS	Assets	Exp.
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.641	0.182	0.419	0.683	0.224	0.261
	(4.412)	(0.430)	(0.510)	(4.671)	(0.429)	(0.519)
Post treatment	-5.118***	0.678***	0.189	-0.593	0.920***	0.396**
	(1.587)	(0.123)	(0.168)	(1.465)	(0.178)	(0.191)
Treatment X Post treatment	0.957	-0.270	0.0208	0.198	-0.536**	-0.415
	(2.740)	(0.198)	(0.305)	(2.799)	(0.215)	(0.387)
Observations	1,168	1,149	1,045	1,372	1,302	1,230
R-squared	0.015	0.022	0.017	0.001	0.032	0.006

Table B.10.1: Treatment effect on policy outcomes (5 km sample)

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer.

B.11 Households never treated

			25 - 40	0 km		
		2016			2019	
Dependent variables	FCS	Assets	Exp.	FCS	Assets	Exp.
	(1)	(2)	(3)	(1)	(2)	(3)
Treatment	1.982	-0.160	0.550	-0.856	0.560	0.301
	(4.879)	(0.306)	(0.662)	(6.661)	(0.782)	(0.576)
Post treatment	-0.584	0.295***	-0.0106	-7.191	0.887	-0.256
	(4.434)	(0.0222)	(0.288)	(4.971)	(0.523)	(0.694)
Treatment X Post treatment	-6.259	-0.169	-0.468	5.772	-0.640	0.318
	(4.857)	(0.162)	(0.430)	(6.132)	(0.573)	(0.752)
Observations	244	236	216	224	217	185
R-squared	0.024	0.010	0.020	0.028	0.044	0.023

Table B.11.1: Treatment effect on policy outcomes (25-40 km sample)

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer.

B.12 Treatment & weather anomalies

			20	16		
Dependent variables		SPEI_{t-1}			SPEI_t	
	No matching	Matching(1)	Matching(2)	No matching	Matching(1)	Matching(2)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.0590	-0.155	-0.256**	-0.182	0.144	0.330
	(0.138)	(0.132)	(0.0946)	(0.203)	(0.204)	(0.262)
Post treatment	0.389***	0.412***	0.429***	-1.170***	-0.986***	-0.976***
	(0.0780)	(0.123)	(0.153)	(0.106)	(0.149)	(0.110)
Treatment X Post treatment	0.214	0.183	0.344	-0.221	-0.413*	-0.362
	(0.343)	(0.337)	(0.323)	(0.199)	(0.219)	(0.224)
Observations	2,273	1,708	1,232	2,273	1,708	1,232
R-squared	0.184	0.201	0.325	0.527	0.548	0.547

Table B.12.1: Effect of the treatment on the SPEI

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching (except for columns 1 & 4). In columns 1-3, the outcome is the SPEI during Malawi's agricultural season, in period t-1 with respect to the household survey. In columns 4-6, the outcome is the SPEI during Malawi's agricultural season, in period t with respect to the household survey. Columns 1 & 4: DiD estimation with no matching. Columns 2 & 5, matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m). Columns 3 & 6, matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), daily market in the community (1=yes), permanent ADMARC (Agricultural Development and Marketing Corporation) market in the community (1=yes), place in the community to purchase common medicines such as pain killers (1=yes), health clinic (Chipatala) in the community (1=yes), post office in the community (1=yes), irrigation scheme in the community (1=yes), community owns a communal forest (1=yes), % under agriculture within ~ 1 km buffer, forest cover (%) - 10 km buffer, elevation (m).

			20	16		
	No shock i	n $_{t-1}$ (SPE	$[t_{t-1} \ge 1)$	No shock	t in $_t$ (SPEI	$_t \ge 1 $)
Dependent variables	FCS	Assets	Exp.	FCS	Assets	Exp.
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	4.862*	-0.00301	-0.0257	4.862*	-0.00301	-0.0257
	(2.621)	(0.241)	(0.244)	(2.620)	(0.241)	(0.244)
Post treatment	-1.734	0.540***	0.0551	-4.200***	0.353**	-0.190
	(1.684)	(0.121)	(0.163)	(1.501)	(0.134)	(0.152)
Treatment X Post treatment	-9.351***	-0.405*	-0.807**	-7.366**	-0.442*	-0.533*
	(3.242)	(0.225)	(0.360)	(3.151)	(0.236)	(0.269)
Observations	1,476	1,441	1,315	1,677	1,626	1,478
R-squared	0.048	0.015	0.030	0.067	0.009	0.029

Table B.12.2: Households that have not experienced a shock

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. In columns 1-3, the sample is comprised of households that have not experienced a weather shock (both treated & untreated), characterized by SPEI values greater than or equal to 1 in absolute value, the year prior to the survey. In columns 4-6, the sample is comprised of households that have not experienced a weather shock, characterized by SPEI values greater than or equal to 1 in absolute value, the year of the survey. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

Dependent variable		Self-report	ed drought	
	20	16	20	19
	Matching(1)	Matching(2)	Matching(1)	Matching(2)
	(1)	(2)	(3)	(4)
Treatment	0.0752	0.0468	0.0674	-0.0139
	(0.0901)	0.0901) (0.118)		(0.103)
Post treatment	0.0249	-0.0263	-0.0726	-0.132**
	(0.0811)	(0.117)	(0.0448)	(0.0609)
Treatment X Post treatment	-0.120	-0.0431	-0.0875	-0.0884
	(0.104)	(0.135)	(0.0916)	(0.0917)
Observations	1,794	1,286	2,498	1,873
R-squared	0.005	0.003	0.017	0.036

Table B.12.3: Effect of the treatment on a self-reported drought measure

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. The outcome is binary self-reported drought measure that takes '1' if households have reported to have experienced a drought in the past year (or in the past three years in the case of the 2019 survey). Columns 1 & 3, matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m). Columns 2 & 5, matching variables: household size, livestock ownership (1=yes), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m). Columns 2 & 5, matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), daily market in the community (1=yes), permanent ADMARC (Agricultural Development and Marketing Corporation) market in the community (1=yes), place in the community to purchase common medicines such as pain killers (1=yes), health clinic (Chipatala) in the community (1=yes), post office in the community (1=yes), irrigation scheme in the community (1=yes), community owns a communal forest (1=yes), % under agriculture within ~ 1 km buffer, forest cover (%) - 10 km buffer, elevation (m).

B.13 Removal of PERFORM districts

		20	016			20	19	
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	2.798	-0.217	-0.209	0.0124	2.856	-0.144	-0.151	0.00648
	(2.698)	(0.200)	(0.229)	(0.0181)	(2.430)	(0.182)	(0.215)	(0.0200)
Post	-2.496	0.455***	-0.0491	0.126*	0.959	0.477***	0.0302	0.102*
	(1.698)	(0.135)	(0.169)	(0.0731)	(1.392)	(0.122)	(0.177)	(0.0571)
Treatment X Post	-6.917**	-0.347*	-0.559**	-0.0368	-4.504**	-0.156	0.0677	-0.0444
	(3.239)	(0.184)	(0.252)	(0.0883)	(1.983)	(0.252)	(0.391)	(0.0674)
Observations	1,628	1,576	1,429	972	1,944	1,847	1,724	1,113
R-squared	0.038	0.023	0.036	0.078	0.006	0.018	0.002	0.083

Table B.13.1: Treatment effect without PERFORM districts (2016 & 2019)

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

B.14 Households' allocation of labor - detail



Figure B.14.1: Heterogeneous impacts based on labor allocation - 2016



Figure B.14.2: Heterogeneous impacts based on labor allocation - 2019

B.15 Regional differences between groups

							201	9						
				CENT	RAL						SOL	JTH		
Variables (measured at baseline)		Treated gro	dn	0	Control gro	dn	t_tost	Г	reated gr	dnc	0	Control gro	dnc	t-toct
	Obs.	Mean	SD	Obs.	Mean	SD	1-1021	Obs.	Mean	SD	Obs.	Mean	SD	1631-1
Policy outcomes														
Food Composition Score	175	48.946	17.790	533	54.524	21.158	5.579***	54	45.509	19.753	329	43.023	16.477	-2.486
Asset value (log. real terms. MWK)	156	8.207	0.148	475	9.478	0.092	1.270^{***}	4	8.262	1.660	271	8.278	0.098	0.015
Non-food expenditures. week (log. real value. MWK)	144	4.330	1.543	500	5.359	1.749	1.029 ***	51	3.800	1.402	316	4.041	4.041	0.241
Forest loss (%)	160	0.053	0.052	210	0.019	0.035	-0.033***	51	0.078	0.061	276	0.036	0.060	-0.042***
Matching variables														
Household size	167	5.377	2.327	436	5.569	2.265	0.191	53	4.528	2.180	315	4.609	1.991	0.081
Livestock ownership $(1=yes)$	167	0.605	0.490	436	0.399	0.490	-0.206***	53	0.472	0.504	315	0.505	0.501	0.6571
Food expenditures (log. real terms. MWK)	164	6.609	1.218	434	7.504	1.292	0.895***	53	6.727	0.610	315	6.412	1.139	-0.315**
Distance to pop. center (km)	167	39.123	14.193	436	21.249	16.340	-17.874***	53	11.093	7.624	315	35.607	14.874	24.514***
Forest cover (%) - 10 km buffer	167	15.798	4.488	436	9.892	4.022	-5.906***	53	19.399	2.739	315	14.038	5.353	-5.361***
Elevation (m)	167	1032.042	331.765	436	1144.206	96.561	112.165***	53	452.491	367.254	315	730.505	144.178	278.014***

Table B.15.1: Differences between groups according to the region - 2016
							201	6						
				CENT	RAL						SOL	HT		
Variables (measured at baseline)		Treated gro	dno	0	Control gro	dn	t_tact	Γ	reated gro	dno	0	control gro	dnc	t tact
	Obs.	Mean	SD	Obs.	Mean	SD	1-1021	Obs.	Mean	SD	Obs.	Mean	SD	1631-1
Policy outcomes														
Food Composition Score	210	49.024	17.329	653	54.252	21.535	5.228***	63	45.198	18.466	392	42.803	16.600	-2.395
Asset value (log. real terms. MWK)	183	8.174	1.825	575	9.447	1.983	1.274^{***}	53	8.293	1.613	326	8.217	1.624	-0.076
Non-food expenditures. week (log. real value. MWK)	176	4.226	1.487	612	5.347	1.736	1.121^{***}	59	3.831	1.371	374	4.153	1.270	0.322^{*}
Forest loss (%)	193	0.056	0.054	253	0.020	0.035	036	58	0.071	0.061	326	0.036	0.063	-0.035
Matching variables														
Household size	210	5.505	2.290	653	5.562	2.221	0.057	63	4.698	2.226	392	4.694	1.965	0.987
Livestock ownership $(1 = yes)$	210	0.6	0.491	653	0.381	0.486	-0.219***	63	0.524	0.503	392	0.495	0.501	-0.029
Food expenditures (log. real terms. MWK)	206	6.579	1.174	650	7.510	1.275	0.931^{***}	63	6.797	0.621	392	6.441	1.120	-0.356**
Distance to pop. center (km)	210	39.871	13.561	653	20.675	15.696	-19.196***	63	10.781	7.924	392	36.646	14.852	25.865***
Forest cover (%) - 10 km buffer	210	16.085	4.687	653	9.918	4.120	-6.166***	63	19.070	2.622	392	14.039	5.393	-5.031***
Elevation (m)	210	1017.257	326.661	653	1135.178	95.930	117.920***	63	472.159	343.444	392	727.523	136.152	255.365***

 Table B.15.2: Differences between groups according to the region - 2019

B.16 Regional analysis on forest outcomes

				2016	5			
		Ce	ntral			So	uth	
Gross forest loss (%)	6 km	10 km	14 km	20 km	6 km	10 km	14 km	20 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.00784	0.0273	0.0286*	0.0339***	0.0226	0.0137	0.0261	0.0408
	(0.0237)	(0.0173)	(0.0143)	(0.0102)	(0.0453)	(0.0316)	(0.0340)	(0.0444)
Post treatment	-0.0228	-0.00625	0.00193	0.0295*	0.239**	0.228**	0.214**	0.192**
	(0.0136)	(0.00813)	(0.00753)	(0.0145)	(0.111)	(0.105)	(0.0935)	(0.0708)
Treatment X Post	0.110**	0.153**	0.134**	0.0866*	-0.196*	-0.124	-0.114	-0.0794
	(0.0494)	(0.0702)	(0.0512)	(0.0499)	(0.113)	(0.108)	(0.0943)	(0.0855)
Observations	1,014	1,014	1,014	1,014	624	624	624	624
R-squared	0.103	0.254	0.391	0.354	0.116	0.131	0.150	0.196

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

				2019	9			
		Ce	ntral			So	uth	
Dependent variables	6 km	10 km	14 km	20 km	6 km	10 km	14 km	20 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.0150	0.0309*	0.0318**	0.0365***	0.0135	0.00729	0.0194	0.0311
	(0.0254)	(0.0173)	(0.0142)	(0.0106)	(0.0436)	(0.0311)	(0.0317)	(0.0408)
Post treatment	-0.00881	0.0107	0.00193	0.00524	0.175*	0.162**	0.145**	0.150***
	(0.0106)	(0.00763)	(0.00579)	(0.00388)	(0.101)	(0.0753)	(0.0547)	(0.0388)
Treatment X Post	0.0954	0.205**	0.188**	0.153***	-0.201*	-0.101	-0.0472	-0.00204
	(0.0701)	(0.0893)	(0.0725)	(0.0555)	(0.106)	(0.0871)	(0.0723)	(0.0875)
Observations	1,246	1,246	1,246	1,246	747	747	747	747
R-squared	0.086	0.353	0.417	0.484	0.092	0.111	0.161	0.289

Table B.16.2: Regional analysis on forest outcomes - 2019

Standard errors in parentheses clustered at the EA level.

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

Notes: DiD estimation using weights from Kernel matching. Matching variables: household size, livestock ownership (1=yes), value of durable goods (log), value of food expenditures (log), household distance to nearest town of > 20,000 pop. (km), forest cover (%) - 10 km buffer, elevation (m).

B.17 Labor options by region



Figure B.17.1: Spatial heterogeneity & labor options - Central region



Figure B.17.2: Spatial heterogeneity & labor options - South region

Appendix C

Appendix for Chapter 3

C.1 Country surveys

List of countries	Years
Burundi	2010; 2016
Cameroon	2004; 2011; 2018
Chad	2004; 2014
Benin	2001; 2006; 2011; 2017
Ethiopia	2000; 2005; 2011; 2016; 2019
Ghana	2003; 2008; 2014
Guinea	2005; 2012; 2018
Kenya	2003; 2008; 2014
Lesotho	2004; 2009; 2014
Liberia	2007; 2013
Madagascar	2003; 2008
Malawi	2000; 2004; 2010; 2016
Mali	2001; 2006; 2012; 2018
Mozambique	2003; 2011
Namibia	2000; 2006; 2013
Niger	2006; 2012
Nigeria	2003; 2008; 2013; 2018
Rwanda	2000; 2005; 2010; 2014
Senegal	2005; 2010; 2012; 2014; 2015; 2016; 2017
Zimbabwe	2005; 2010; 2015
Togo	2013
Uganda	2001; 2006; 2011; 2016
Tanzania	2004; 2010; 2015
Burkina Faso	2003; 2010
Zambia	2001; 2007; 2013; 2018

Table C.1.1: Country surveys used in the analysis

SWPER individual items **C.2**

Table C.2.1: Variables used to develop the SWPER

Variables	Code/Unit
Beating not justified if wife goes out without telling husband	Justified=–1; don't know=0; not justified =1
Beating not justified if wife neglects the children	Justified=-1; don't know=0; not justified =1
Beating not justified if wife argues with husband	Justified=-1; don't know=0; not justified =1
Beating not justified if wife refuses to have sex with husband	Justified=-1; don't know=0; not justified =1
Beating not justified if wife burns the food	Justified=-1; don't know=0; not justified =1
Frequency of reading newspaper or magazine	Not at all=0; <once a="" week="1;<math">\geqonce a week=2</once>
Respondent worked in the past 12 months	No=0; in the past year=1; have a job,
	but on leave past 7 days=2; currently working=2
Woman's education in completed years of schooling	Years
Education difference: woman's minus husband's years of schooling	Years
Age difference: woman's age minus husband's age	Years
Age of woman at first cohabitation	Years
Age of woman at first birth*	Years
Who usually decides on respondent's health care	Husband or other alone=-1; joint=0;respondent alone=1
Who usually decides on large household purchases	Husband or other alone=-1; joint=0;respondent alone=1
Who usually decides on visits to family or relatives	Husband or other alone=-1; joint=0;respondent alone=1

Source: Ewerling et al. (2017) *Notes*:*imputed for women who did not have any children.

C.3 SWPER item weights

Table C.3.1: Variable weights used for SWPER individual scores

Items	Attitude to violence	Autonomy	Decision making
Beating not justified if wife goes out without telling husband	0.489	-0.006	-0.001
Beating not justified if wife neglects the children	0.493	-0.020	-0.040
Beating not justified if wife argues with husband	0.501	0.000	0.007
Beating not justified if wife refuses to have sex with husband	0.493	0.000	0.026
Beating not justified if wife burns the food	0.546	-0.003	-0.014
Frequency of reading newspaper or magazine	0.056	0.549	0.150
Respondent worked in the past 12 months	0.015	0.090	0.026
Woman's education in completed years of schooling	-0.008	0.141	-0.019
Education difference: woman's minus husband's years of schooling	-0.004	0.131	-0.006
Age difference: woman's age minus husband's age	0.002	0.026	0.012
Age of woman at first cohabitation	-0.004	0.050	-0.009
Age of woman at first birth	0.008	0.004	0.770
Who usually decides on respondent's health care	-0.034	-0.013	0.831
Who usually decides on large household purchases	0.008	-0.052	0.768
Who usually decides on visits to family or relatives	0.001	-0.060	0.180

Source: Ewerling et al. (2017)

C.4 WHZ & decision making - country ranking



Figure C.4.1: Mean WHZ of children aged 0-59 months per country



Figure C.4.2: Mean of women's decision power score per country

C.5 Decision making tertiles

Dependent variables Variables	WHZ (1)	Wasting (2)
Heat exposure (>30 $^{\circ}$ C)	-0.138***	0.0131***
	(0.0225)	(0.00411)
Decision making tertiles (ref: 1 st tertile)		
2 nd tertile	0.0127	-0.00211
	(0.0123)	(0.00212)
3 rd tertile	0.00906	0.00157
	(0.0127)	(0.00222)
Heat X Decision making (ref: 1 st tertile)		
Heat X Decision making (2 nd tertile)	0.0377**	-0.00958***
-	(0.0171)	(0.00340)
Heat X Decision making (3 rd tertile)	0.0159	-0.00881**
-	(0.0187)	(0.00364)
Child characteristics	\checkmark	\checkmark
Maternal characteristics	\checkmark	\checkmark
Household characteristics	\checkmark	\checkmark
Climate control	\checkmark	\checkmark
Region X Month	\checkmark	\checkmark
Region X Year	\checkmark	\checkmark
Observations	000 050	
UDServations	238,253	238,253
K-squared	0.089	0.068

Table C.5.1: Main results with decision making tertiles

Robust standard errors in parentheses clustered at the EA level *** p<0.01, ** p<0.05, * p<0.1

Notes: Linear model with high dimensional fixed-effects by Correia (2017). Fixed effects are with respect to the month and year of the interview.

C.6 Alternative decision making measure

 Dependent variables	WHZ.	Wasting
Variables	(1)	(2)
Heat exposure (>30 $^{\circ}$ C)	-0.141***	0.0121***
	(0.0218)	(0.00398)
Decision making (ref: none)	0.00939	-0.000248
	(0.0113)	(0.00196)
Heat X Decision making	0.0374**	-0.00958***
	(0.0156)	(0.00307)
Child characteristics	\checkmark	\checkmark
Maternal characteristics	\checkmark	\checkmark
Household characteristics	\checkmark	\checkmark
Climate control	\checkmark	\checkmark
Region X Month	\checkmark	\checkmark
Region X Year	\checkmark	\checkmark
Ohannatiana	047 704	047 704
Observations	247,724	247,724
R-squared	0.089	0.069

Table C.6.1: Main results with alternative decision making indicator

Robust standard errors in parentheses clustered at the EA level

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

Notes: Linear model with high dimensional fixed-effects by Correia (2017). Fixed effects are with respect to the month and year of the interview.

C.7 Attitude to violence and social independence

Table C.7.1: Main results with the two other dimensions of the SWPER

Dependent variable: WHZ Variables WHZ (1) Warsing (2) WHZ (3) Warsing (4) Heat exposure (>30 °C) -0.119*** (0.00488) 0.005385 (0.00318) -0.0126** (0.00731) 0.001250 (0.00132) 0.001365 (0.00132) 0.001375 (0.00132) 0.001375 (0.00132) 0.001375 (0.00132) 0.001375 (0.00132) 0.001375 (0.001255) 0.001325 (0.007251) 0.001325 (0.007251) 0.001375 (0.001255) 0.001375 (0.00137) 0.001375 (0.00137) 0.001375 (0.00137) 0.001375 (0.00137) 0.001375 (0.00137) 0.001375 (0.00111) 0.001375 (0.00111) 0.001475 (0.00111) 0.001375 (0.00111) 0.001475 (0.00111) 0.001375 (0.00111) 0.001475 (0.00111) 0.001375 (0.00111) 0.001747 (0.00174) 0.001747 (0.00174)		Attitude	to violence	Auto	nomy
Heat exposure (>30 °C) -0.119*** 0.00598* -0.126*** 0.00726** Empowerment 0.00977* 0.00125 0.0316*** -0.0304*** 0.000319 Heat exposure X Empowerment 0.00319 -0.0246* -0.0113 -0.00132 Child characteristics (0.000255) Colos205 -0.00325*** -0.00187** Child's age (months) 0.00318*** -0.00186*** 0.00325*** -0.00187** Child's sex (ref: female) -0.0229*** 0.00157* (0.000255) (0.000255) (0.000257) Birth order (count) 0.0899*** -0.0015*** 0.0789*** -0.00582*** Mother's age (years) -0.000412 (0.00017) (0.000541) (0.00017) Mother's deducation (years) -0.0122*** -0.0026*** (0.00017) Mother's education (years) 0.0122*** -0.0026*** 0.000173** Number of children under five (count) 0.0252*** 0.00152* (0.00074) (0.0010) (0.00225) (0.000471) (0.00254) (0.00175) Sanitation type (ref: Flish)	Dependent variable: WHZ Variables	WHZ (1)	Wasting (2)	WHZ (3)	Wasting (4)
Heat exposure (>30 °C) -0.119*** 0.00589* -0.126*** 0.00726** (0.0185) (0.00318) (0.0186) 0.00316*** -0.00314** (0.00318) (0.00183) (0.00386) 0.00316*** -0.00314** (0.00131) (0.00145) (0.00731) (0.00185) (0.00171) (0.00145) (0.00731) (0.00152) (0.00152) Child characteristics (0.00255) (5.02e-05) (0.00256) (5.056-05) Child's sex (ref: female) -0.0229*** -0.00154*** -0.00158** -0.001529 Birth order (count) (0.809*** -0.00151*** 0.000309*** (0.000741) (0.00120) (0.00137) (0.00036)**** -0.00158*** Mother's age (years) -0.000412 0.000121 -0.00154*** 0.00039*** (0.000471) (0.000411) (0.000111) (0.000111) (0.000111) (0.000111) (0.000111) (0.000111) (0.000111) (0.000111) (0.0007*** -0.00056 (0.00036)**** (0.00124)* (0.00113) (0.00111) (0.0007**) (0.00111) (0.0007**) (0.00111) (0.0007**) (0.0007**) (0.0007**)<					
(0.0185) (0.00318) (0.0186) (0.00318) Empowerment (0.00125) (0.00314)** -0.00314*** Heat exposure X Empowerment (0.00731) (0.00145) (0.00071)* Child's age (months) (0.001318*** (0.00125) (0.00256) (0.00256) (0.00257) Child's sex (ref: female) -0.0229*** 0.00255) (0.000574) (0.001574) (0.000574) (0.00120) Birth order (count) (0.00574) (0.00127) (0.00255) (0.00127) (0.00256) (0.00120) Birth order (count) (0.00574) (0.00127) (0.000557) (0.00110) Mother's age (years) -0.000471 (9.098-05) (0.000141) (0.000111) Mother's education (years) 0.0122*** -0.0026**** -0.000592*** (0.000747) Sex of household head (ref: female) 0.0122*** -0.00180*** 0.00111 (0.000747) Sex of household head (ref: female) 0.0124** -0.000560 0.0164** -3.79e-05 Other 0.0124 -0.01110 (0.00225) (0.00074)<	Heat exposure (>30 °C)	-0.119***	0.00598*	-0.126***	0.00726**
Empowerment 0.00977^{++} 0.00125 0.0316^{+++} -0.00344^{+++} (0.00483) (0.000866) (0.00720) (0.000915) (0.000915) Heat exposure X Empowerment 0.00319 -0.00246^{+} -0.0113 -0.00132 Child characteristics (0.000255) (0.000255) (0.000255) (0.000255) (0.000255) (0.000255) (0.000256) (0.00120) (0.00074) (0.00120) (0.000256) (0.00120) (0.000574) (0.00654) (0.00120) (0.00120) (0.00120) (0.00120) (0.00121) (0.00121) (0.000574) (0.000574) (0.000171) (0.0001138) Maternal characteristics (0.000471) (0.000471) (0.000471) (0.000541) (0.000113) Mother's deucation (years) 0.0122*** 0.00126** (0.00173** (0.000747) (0.000747) Sex of household head (ref: female) 0.0122** 0.00152** 0.00164** 3.79e.05 Source of drinking water (ref: Piped) Well (0.0118) (0.00225) (0.01124) (0.001124) (0.00124) (0		(0.0185)	(0.00318)	(0.0186)	(0.00318)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Empowerment	0.00977**	0.00125	0.0316***	-0.00304***
Heat exposure A Empowerment 0.00319 -0.00426 -0.0113 -0.00132 Child's age (months) (0.00731) (0.00731) (0.00781) (0.00781) (0.00125) Child's age (months) (0.00225)* (5.02e-05) (0.00225)* (5.02e-05) (0.00226)** (0.00129*** Child's sex (ref: female) -0.0229*** (0.00129)** (0.00129)*** (0.00138) Maternal characteristics (0.00683) (0.00683) (0.000110) (0.000570)*** -0.00582*** Mother's age (years) -0.00252*** (0.000531)*** (0.000531)*** (0.000570)*** -0.000593*** Mother's education (years) 0.0122*** -0.000522** (0.000741) (0.000741) (0.000747) Sex of household head (ref: female) 0.00352*** (0.00152) (0.000741) (0.00173) Source of drinking water (ref: Piped) Well -0.00238** 0.00112 (0.00174) (0.00124) Wealth quintiles (ref: Flush) Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 Middle 0.0575*** -0.01144 <td>II</td> <td>(0.00483)</td> <td>(0.000866)</td> <td>(0.00520)</td> <td>(0.000917)</td>	II	(0.00483)	(0.000866)	(0.00520)	(0.000917)
Child characteristics (0.00131) (0.00132) (0.00132) Child's age (months) 0.0018^{***} 0.00186^{***} 0.00225^{***} 0.0129^{***} 0.00225^{***} 0.0129^{***} 0.00225^{***} 0.0129^{***} 0.00225^{***} 0.0129^{***} 0.00225^{***} 0.0129^{***} 0.00574 0.00574 0.0007120 0.001220^{***} 0.000525^{***} 0.001220^{***} 0.000525^{***} 0.000525^{***} 0.000525^{***} 0.000520^{***} 0.000558^{***} 0.000558^{***} 0.000558^{***} 0.000554^{***} 0.000554^{***} 0.000574^{***} 0.000574^{***} 0.000574^{***} 0.000554^{***} 0.000554^{***} 0.000554^{***} 0.000554^{***} 0.000554^{***} 0.000554^{***} 0.000746^{*} 0.000747^{*} 0.00173^{**} Mother's education (years) 0.0252^{***} 0.00152^{**} 0.00173^{**} 0.000747^{*} 0.00173^{**} Number of children under five (count) 0.0252^{***} 0.00152^{**} 0.00173^{**} 0.00173^{**} 0.00173^{**} 0.00174^{**} Sex of household head (ref: female)	Heat exposure x Empowerment	(0.00319)	-0.00246 [^]	-0.0113	-0.00132
Child's age (months) 0.00318^{***} 0.00186^{***} 0.00325^{***} 0.00325^{***} 0.000255 $(5.02e-05)$ (0.000255) $(5.02e-05)$ (0.000255) $(5.02e-05)$ (0.00120) (0.00110) (0.000110) (0.000110) (0.00011) (0.00011) (0.00011) (0.00011) (0.00011) $(0.000174)^*$ $(0.00174)^*$ $(0.00174)^*$ $(0.00174)^*$ $(0.00174)^*$ (0.00180) (0.00180) Sex of household head (ref: female) 0.0122^{***} 0.00122^{***} (0.00120) (0.00180) (0.00120) (0.00120) (0.00120)	Child characteristics	(0.00/31)	(0.00145)	(0.00/81)	(0.00152)
Initial or	Child's age (months)	0.00318***	-0.00186***	0.00325***	-0.00187***
Child's sex (ref: female) -0.0229^{***} 0.0129^{***} 0.0129^{***} 0.0129^{***} Birth order (count) 0.000574) (0.00120) (0.00574) (0.00120) Maternal characteristics (0.00137) (0.00683) (0.00137) (0.000476) (0.00010) Mother's age (years) -0.000412 0.000121 -0.00154^{***} $(0.00039)^{***}$ Mother's height (cm) 0.00532^{***} 0.000253^{***} 0.000541 (0.000111) Mother's education (years) 0.0122^{***} -0.00208^{***} 0.000746 (0.000352) Mumber of children under five (count) -0.0235^{***} 0.000746 (0.00352) (0.000746) (0.00747) Sex of household head (ref: female) 0.0193^{**} -0.000560 0.0164^{**} $3.79e-05$ Source of drinking water (ref: Piped) 0.0124^{**} 0.00119 0.00237^{**} 0.00124^{**} Well 0.0124^{**} 0.00129^{**} 0.00154^{**} 0.00124^{**} Vell 0.00136^{**} 0.00136^{**} 0.00124^{**} 0.00225^{**} Other 0.0124^{**} $0.00113^$	cinia o ago (montaio)	(0.000255)	(5.02e-05)	(0.000256)	(5.05e-05)
	Child's sex (ref: female)	-0.0229***	0.0129***	-0.0228***	0.0129***
Birth order (count) 0.0803^{+++} 0.00683 0.00789^{+++} 0.00582^{+++} Maternal characteristics 0.000471 0.000121 0.00134^{+++} 0.00039^{+++} Mother's age (years) 0.00535^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000570^{+++} 0.000740^{+} (0.000111) Mother's education (years) 0.0122^{+++} 0.000216^{+++} 0.00074^{++} 0.00074^{++} 0.00173^{++} Number of children under five (count) -0.0252^{+++} 0.00152^{++} 0.000740^{+} $(0.00130)^{-}$ $(0.00747)^{-}$ Sex of household head (ref: female) 0.0193^{++} -0.000500^{-} $(0.00180)^{-}$ $(0.00180)^{-}$ $(0.00180)^{-}$ $(0.00180)^{-}$ $(0.00180)^{-}$ $(0.0022)^{-}$ $(0.0015)^{-}$ $(0.00120)^{-}$ Source of drinking water (ref: Fiped) u u $(0.0118)^{-}$ $(0.00225)^{-}$ (0.015^{-}) $(0.00225)^{-}$ $(0.0123)^{-}$ $(0.00247)^{-}$		(0.00574)	(0.00120)	(0.00574)	(0.00120)
Maternal characteristics Mother's age (years) (0.00683) (0.00137) (0.00685) $(0.0036)^{***}$ Mother's height (cm) (0.00471) $(9.98e-05)$ (0.00070^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000570^{***}) (0.000747) Mumber of children under five (count) (0.0122^{***}) (0.00152^{***}) (0.000747) (0.00747) Sex of household head (ref: female) (0.193^{***}) (0.00123) (0.000747) (0.000747) Source of drinking water (ref: Piped) (0.0124) (0.00180) (0.0022) (0.00121) Well (0.0124) (0.00140) (0.0114) (0.0022) (0.0022) Other (0.0124) (0.00140) (0.0114) (0.0022) Other (0.0154) (0.00366) (0.0175) (0.00347) Other (0.0154) (0.00346) (0.0175) (0.00377) Other (0.0197) (0.0193) (0.0175) (0.00348) Other (0.0197) (0.0121) (0.00225) (0.0112) Other (0.0197) (0.00219) (0.0177) (0.00219) Other (0.0197) (0.00219) (0.0177) (0.00219) Other (0.0197) (0.00219) <t< td=""><td>Birth order (count)</td><td>0.0809***</td><td>-0.00615***</td><td>0.0789***</td><td>-0.00582***</td></t<>	Birth order (count)	0.0809***	-0.00615***	0.0789***	-0.00582***
Maternal characteristics 0.000412 0.000121 0.00136^{+**} 0.00039^{+**} Mother's age (years) 0.000536^{+**} 0.000535^{+**} 0.000579^{+**} 0.000593^{+**} Mother's height (cm) 0.00122^{+**} 0.000208^{+**} 0.000500^{+**} 0.000500^{+**} Mother's education (years) 0.0122^{+**} 0.000208^{+**} 0.00024^{+**} 0.000746^{+} 0.000747^{+} Mumber of children under five (count) 0.0252^{+**} 0.00152^{+*} 0.0026^{+**} 0.00173^{+*} Sex of household head (ref: female) 0.0193^{+*} -0.002660 0.0164^{+} $3.79e-05$ Source of drinking water (ref: Piped) Well 0.00124 0.00110 (0.00180) Well 0.0124 0.00140 0.0114 0.00124 Vell 0.0124 0.00148 0.00225 (0.0118) (0.00202) Other 0.0124 0.00480 0.0154 0.00225 (0.0118) (0.00225) Sanitation type (ref: Flush) 0.0077 0.00448^{+*} 0.0242^{+*}		(0.00683)	(0.00137)	(0.00685)	(0.00138)
Mother's age (years) -0.00412 0.000121 -0.00154*** 0.000309*** Mother's height (cm) $(0.000536^{***} - 0.000535^{***} - 0.000579^{***} - 0.000593^{***}$ (0.000542) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.000541) (0.00052) (0.000746) (0.000746) (0.000747) Sex of household head (ref: female) 0.0193^{**} -0.000560 0.0164^{**} $3.79e-05$ Source of drinking water (ref: Piped) well -0.0232^{**} 0.00140 0.0114 -0.00121 Well -0.0238^{**} 0.00140 0.0114 -0.00121 0.00140 0.0124 Other 0.0124 -0.0140 0.0114 -0.00121 0.00170 0.00225 0.0114 0.00274 Other 0.0175 0.00346 -0.0153 -0.00274 0.00496 -0.0121^{**}	Maternal characteristics				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Mother's age (years)	-0.000412	0.000121	-0.00154***	0.000309***
Mother's neight (cfn) 0.00530^{-xx} 0.000530^{-xx} 0.000530^{-xx} 0.000500^{-xx} 0.000000^{-xx} 0.000000^{-xx} 0.000000^{-xx} 0.000000^{-xx} 0.00000^{-xx} 0.000000^{-xx} 0.0000000^{-	March and Instally (and)	(0.000471)	(9.98e-05)	(0.000476)	(0.000101)
Mother's education (years) (0.00342) (0.00028^{+++}) (0.000341) (0.000111) Household characteristicsNumber of children under five (count) -0.0252^{+++} (0.00152^{++}) (0.00352) (0.000747) Sex of household head (ref: female) 0.0193^{++} -0.000560 0.0164^{++} $3.79e-05$ Source of drinking water (ref: Piped) (0.00352) (0.00110) (0.00931) (0.00180) Well -0.0238^{++} 0.00119 -0.0237^{++} 0.00124 Well -0.0238^{++} 0.00114 -0.00121 Other 0.0124 -0.00440 0.0114 (0.00225) Other 0.0124 -0.00436 -0.0153 -0.0027^{+} Intarine (0.0154) (0.00306) (0.0154) (0.00307) Other -0.00489 -0.00436 -0.0153 -0.00274 Potrer (0.0154) (0.00306) (0.0154) (0.00307) Other 0.0044^{+} 0.0014^{+} 0.00409 (0.0175) (0.00348) Wealth quintiles (ref: Poorest) $(0.0191^{+})^{+}$ -0.00448^{+*} 0.0242^{+*} -0.00525^{+*} Porer 0.0191^{+} -0.019^{+**} 0.0736^{+**} -0.0121^{+**} (0.0123) (0.02245) (0.0111) (0.00225) (0.0123) Middle 0.0575^{+**} -0.0119^{+**} 0.0736^{+**} -0.0121^{+**} (0.0123) (0.0245) (0.0123) (0.00245) (0.00245) Richest 0.0575^{+**} $-$	Mother's height (cm)	0.00536^^^	-0.000535^^^	$0.005/0^{-1}$	-0.000593^^^
Mother's education (years) 0.0122 -0.0203 (0.00110) (0.000216) Household characteristics Number of children under five (count) -0.0252^{***} 0.00152^{**} -0.0264^{***} 0.00173^{**} Sex of household head (ref: female) 0.0193^{**} -0.000560 0.0164^{*} $-3.79e-05$ Source of drinking water (ref: Piped) 0.0238^{**} 0.00110 (0.00202) (0.0105) (0.00202) Other 0.0124 -0.00140 0.0114 -0.0021^{**} 0.00122 Other 0.0124 -0.00140 0.0114 -0.0021^{**} Vell (0.0154) (0.00202) (0.0118) (0.00225) Sanitation type (ref: Flush) -0.00489 -0.00436 -0.0153 -0.0027^{**} Pit latrine -0.00489 -0.00448^{**} 0.0242^{**} -0.00332^{**} Other -0.00448^{**} 0.0242^{**} -0.00348 0.0175 0.00322^{**} Other -0.0191^{**} 0.00448^{**} 0.0242^{**} -0.0121^{***} Poorer 0.0191^{**} 0.00488^{*	Mather's advantion (veges)	(0.000542)	(0.000111)	(0.000541)	(0.000111)
(0.00110) (0.001210) Household characteristics Number of children under five (count) -0.0252^{***} 0.00152^{**} -0.0264^{***} 0.000747) Sex of household head (ref: female) 0.0193^{**} 0.000560 0.0164^{**} $3.79e-05$ Source of drinking water (ref: Piped) Well -0.0238^{**} 0.00119 -0.0237^{**} 0.00124 Well -0.0238^{**} 0.00119 -0.0237^{**} 0.00124 Other 0.0124 -0.00140 0.0114 -0.00121 Other 0.0124 -0.00440 0.0114 -0.00222) Other 0.0124 -0.00440 0.0114 -0.00121 Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 Other -0.0304^{*} 0.00193 -0.0441^{**} 0.00499 Porer 0.0191^{**} 0.00448^{**} 0.0225^{**} 0.00177 (0.00306) Middle 0.0575^{***} -0.0107^{**} 0.0676^{***} -0.0122^{**} 0.00242^{**} 0.00224^{**} Middle	Mother's education (years)	(0.0122)	(0.00208)		
Number of children under five (count) -0.0252^{+**} 0.00152^{**} -0.0264^{+**} 0.00173^{**} Number of children under five (count) 0.0252^{+**} 0.00152^{+*} -0.00260^{+**} 0.00173^{**} Sex of household head (ref: female) 0.0193^{**} -0.000560 0.0164^{**} $-3.79e-05$ Source of drinking water (ref: Piped) (0.00180) (0.00180) (0.00202) (0.0105) Well -0.0238^{**} 0.00119 -0.0237^{**} 0.00124 Other 0.0124 -0.0140 0.0114 -0.00121 Other 0.0124 -0.00436 -0.0153 -0.0027^{*} Pit latrine 0.0014^{*} 0.0013^{*} 0.00436 -0.0154^{*} 0.00436 Vealth quintiles (ref: Poorest) Poorer 0.0191^{*} -0.00448^{**} 0.00242^{*} -0.00532^{**} Middle 0.0557^{***} -0.0105^{***} -0.010211^{***} 0.00242^{**} -0.00232^{***} Middle 0.0557^{***} -0.01023^{***} 0.01123^{**} 0.00245^{*}	Household characteristics	(0.00110)	(0.000210)		
Sex of household head (ref: female) (0.00352) (0.000746) (0.00352) (0.00747) Sex of household head (ref: female) 0.0193^{**} -0.000560 0.0164^* $-3.79e-05$ Source of drinking water (ref: Piped) (0.00180) (0.00931) (0.000931) (0.000931) Well -0.0238^{**} 0.00119 -0.0237^{**} 0.00124 Other 0.0124 -0.00140 0.0114 -0.00121 Other 0.0124 -0.00436 -0.0133 -0.00274 Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 Other -0.0304^* 0.00132 -0.0441^{**} 0.000377 Other -0.0304^* 0.00133 -0.00474 0.00193 Other -0.0304^* 0.00175 (0.00306) (0.0153) Other 0.0191^* -0.00448^{**} 0.00242^{**} -0.00532^{**} Poorer 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Poorer 0.0191^* -0.0048^{**} -0.0121^{***} Middle 0.0575^{***} -0.0155^{***} -0.0121^{***} Niddle 0.0575^{***} -0.0155^{***} -0.0121^{***} Niddle 0.0575^{***} -0.0155^{***} -0.0121^{***} Poorer 0.0191^* -0.00448^{**} -0.00242^{**} Niddle 0.0575^{***} -0.0119^{***} -0.00242^{**} Niddle 0.0575^{***} -0.0119^{***} -0.00232^{***} Niddle 0.00213 $(0.0023$	Number of children under five (count)	-0.0252***	0.00152**	-0.0264***	0.00173**
Sex of household head (ref: female) 0.0193^{**} (0.00930) -0.000560 (0.00180) 0.0164^{*} (0.00931) $-3.79e-05$ (0.00180)Source of drinking water (ref: Piped) -0.0238^{**} (0.0105) 0.00119 (0.00202) -0.0237^{**} (0.0105) 0.00124 (0.00202)Well -0.0238^{**} (0.0105) 0.00119 (0.00202) -0.0237^{**} (0.0105) 0.00124 (0.00202)Other 0.0124 (0.0118) -0.0237^{**} (0.00225) 0.0114 (0.0118) -0.00121 (0.00225)Sanitation type (ref: Flush) Pit latrine -0.00489 (0.0154) -0.00436 (0.0153) -0.00274 (0.00306)Other -0.0304^{*} (0.0175) 0.00441^{**} (0.00306) 0.0153 (0.00348)Wealth quintiles (ref: Poorest) Poorer 0.0191^{*} (0.0117) -0.00448^{**} (0.00129) 0.01077 (0.00219)Middle 0.0575^{***} (0.0112) 0.0076^{***} (0.00225) -0.0122^{***} (0.0123) 0.00224^{**} (0.00224)Richer 0.0557^{***} (0.0123) 0.0123 (0.00245) 0.0123 (0.00245) 0.0123 (0.00245)Richest 0.0941^{***} (0.0120) 0.00287^{**} (0.00238) -0.00287^{***} (0.0120) 0.00238 Climate control Precipitation (ref: <100 mm) 100-200 0.130^{***} (0.0220) 0.03366 (0.0331) 0.0220 (0.00386)200-300 0.148^{****} (0.0220) 0.00387^{***} (0.0667) 0.0028^{****} (0.00667) 0.0025^{****} (0.00667)>300 0.100 (0.00677) 0.0027^{***} <b< td=""><td></td><td>(0.00352)</td><td>(0.000746)</td><td>(0.00352)</td><td>(0.000747)</td></b<>		(0.00352)	(0.000746)	(0.00352)	(0.000747)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Sex of household head (ref: female)	0.0193**	-0.000560	0.0164*	-3.79e-05
Source of drinking water (ref: Piped) Well -0.0238^{**} 0.00119 -0.0237^{**} 0.00124 (0.0105) (0.00202) (0.0105) (0.00202) Other 0.0124 -0.00140 0.0114 -0.00121 (0.0118) (0.00225) (0.0118) (0.00225) Sanitation type (ref: Flush) Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 (0.0154) (0.00306) (0.0154) (0.00307) Other -0.0304^{*} 0.0193 -0.0441^{**} 0.00409 (0.0175) (0.00348) (0.0175) (0.00348) Wealth quintiles (ref: Poorest) Poorer 0.0191^{*} -0.00448^{**} 0.0242^{**} -0.00532^{**} (0.0107) (0.00219) (0.0107) (0.00219) Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0124^{***} Richest 0.0941^{***} -0.0173^{***} 0.123^{***} -0.0232^{***} (0.0123) (0.00245) (0.0123) (0.00245) Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0120) (0.00238) (0.0120) (0.00238) Climate control Precipitation (ref: <100 mm) 100-200 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} (0.0120) (0.00238) (0.0120) (0.00238) 200-300 0.148^{***} -0.0242^{***} 0.157^{***} -0.0205^{***} (0.0120) (0.00238) (0.0120) (0.00238) 200-300 0.148^{***} -0.0242^{***} 0.177^{***} -0.0255^{***} (0.0120) (0.00238) (0.0120) (0.00238) 200-300 0.148^{***} -0.0242^{***} 0.177^{***} -0.0255^{***} (0.0120) (0.00286) (0.0220) (0.00388) 200-300 0.148^{***} -0.0242^{***} 0.177^{***} -0.0255^{***} (0.0120) (0.00277) (0.0332) (0.00609) > 300 0.100 -0.0227^{***} 0.107 -0.0225^{***} (0.0667) (0.00969) (0.0667) (0.00969)		(0.00930)	(0.00180)	(0.00931)	(0.00180)
Well -0.0238^{**} 0.00119 -0.0237^{**} 0.00124 Other (0.0105) (0.00202) (0.0105) (0.00202) Other 0.0124 -0.00140 0.0114 -0.00121 (0.0118) (0.00225) (0.0118) (0.00225) Sanitation type (ref: Flush) -0.00489 -0.00436 -0.0153 -0.00274 Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 (0.0154) (0.00306) (0.0154) (0.00307) Other -0.0304^* 0.00193 -0.0441^{**} 0.00409 Porer 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Poorer 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Middle 0.0575^{***} -0.0105^{***} 0.0121 (0.00229) Middle 0.0557^{***} -0.0105^{***} 0.0121^{***} -0.0122^{***} Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} (0.0123) (0.00245) (0.0123) (0.00245) Richest 0.0941^{***} -0.0173^{***} 0.122^{***} -0.0232^{***} (0.0120) (0.00238) (0.0120) (0.00238) Climate control (0.0220) (0.00386) (0.0220) (0.00388) 200^{-300} 0.130^{***} -0.0242^{***} 0.107^{***} -0.0225^{***} >300 0.100 -0.0227^{***} 0.107 -0.0225^{***} >300 0.100 <td< td=""><td>Source of drinking water (ref: Piped)</td><td></td><td></td><td></td><td></td></td<>	Source of drinking water (ref: Piped)				
Other (0.0105) (0.00202) (0.0105) (0.00202) Other 0.0124 -0.00140 0.0114 -0.00121 (0.0118) (0.00225) (0.0118) (0.00225) Sanitation type (ref: Flush) (0.0154) (0.00306) (0.0154) (0.00307) Other $-0.0304*$ 0.00193 $-0.0441**$ 0.00409 (0.0175) (0.00348) (0.0175) (0.00348) Wealth quintiles (ref: Poorest) (0.0107) (0.00225) (0.0117) Poorer $0.0191*$ $-0.0048**$ $0.0242**$ $-0.00532**$ (0.0107) (0.00219) (0.0107) (0.00219) Middle $0.0575***$ $-0.0105***$ $0.0676***$ $-0.0121***$ (0.0111) (0.00225) (0.0112) (0.00224) Richer $0.0557***$ $-0.0119***$ $0.0736***$ $-0.0121***$ (0.0123) (0.00245) (0.0123) (0.00245) (0.00245) Richest $0.0941***$ $-0.0173***$ $0.129***$ $-0.0232***$ (0.0120) (0.00245) (0.0120) (0.00245) (0.00245) Residence (ref: rural) -0.0122 -0.00189 -0.00877 -0.00343 (0.0120) (0.0220) (0.0331) (0.00245) (0.00238) Climate control (0.0220) (0.0331) (0.00607) (0.0332) (0.000388) $200-300$ $0.130***$ $-0.0287***$ 0.107 $-0.0225***$ >300 0.100 $0.0287***$ 0.107 <td< td=""><td>Well</td><td>-0.0238**</td><td>0.00119</td><td>-0.0237**</td><td>0.00124</td></td<>	Well	-0.0238**	0.00119	-0.0237**	0.00124
Other 0.0124 -0.00140 0.0114 -0.00121 Sanitation type (ref: Flush) (0.0118) (0.00225) (0.0118) (0.00225) Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 Other -0.0304^{*} (0.0193) -0.0441^{**} (0.00307) Other $0.0175)$ (0.00348) (0.0175) (0.00348) Wealth quintiles (ref: Poorest) 0.0191^{*} -0.00448^{**} 0.0242^{**} -0.00532^{**} Poorer $0.0175)$ (0.00219) (0.0177) (0.00219) Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Nicher 0.0557^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Richer 0.0557^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0123) (0.00245) (0.0123) (0.00245) (0.00245) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.00343 (0.0120) (0.00238) (0.0120) (0.00238) (0.00238) Climate controlPrecipitation (ref: <100 mm)		(0.0105)	(0.00202)	(0.0105)	(0.00202)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Other	0.0124	-0.00140	0.0114	-0.00121
Samination type (ref. Fush)Pit latrine -0.00489 -0.00436 -0.0153 -0.00274 Other -0.0304^* (0.00306) (0.0154) (0.00307) Other -0.0304^* 0.00193 -0.0441^{**} 0.00409 Wealth quintiles (ref: Poorest) 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Poorer 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} (0.0111) (0.00225) (0.0112) (0.00224) Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} (0.0123) (0.00245) (0.0123) (0.00245) (0.0123) Residence (ref: rural) -0.0122 0.00189 -0.003877 -0.00343 $100-200$ 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} $0.0220)$ (0.0331) (0.06077) (0.0332) (0.00297) $200-300$ 0.148^{***} -0.0242^{***} 0.157^{***} -0.0225^{***} $0.0331)$ (0.00677) (0.0332) (0.0069) > 300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.0969) (0.0667) (0.00969) $Precipin X Month$ \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark	Somitation type (ref. Flush)	(0.0118)	(0.00225)	(0.0118)	(0.00225)
In failing 0.00409 0.00306 0.0153 0.00274 Other (0.0154) (0.00306) (0.0153) (0.00307) Other -0.0304^* 0.00193 -0.0441^{**} 0.00409 Poorer $0.0175)$ (0.00219) (0.0175) (0.00348) Wealth quintiles (ref: Poorest) 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Poorer 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} (0.0107) (0.00219) (0.0107) (0.00219) Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} (0.0111) (0.00225) (0.0112) (0.00224) Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} (0.0123) (0.00245) (0.0123) (0.00245) Residence (ref: rural) -0.0122 0.000189 -0.00232^{***} (0.0120) (0.00238) (0.0120) (0.00238) Climate controlPrecipitation (ref: <100 mm)	Dit latring	-0.00489	-0.00436	-0.0153	-0.00274
Other $(0.010^{+})^{-1}$ $(0.0019^{-})^{-1}$ $(0.0040^{+})^{-1}$ Wealth quintiles (ref: Poorest) 0.0175) (0.00348) (0.0175) (0.00348) Poorer 0.0191^{*} -0.00448^{**} 0.0242^{**} -0.00532^{**} Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} (0.0111) (0.00225) (0.0112) (0.00224) Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} (0.0123) (0.00245) (0.0123) (0.00224) Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0155) (0.00301) (0.0123) (0.00227) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 (0.0120) (0.00238) (0.0120) (0.00238) (0.0120) (0.00238) Climate controlPrecipitation (ref: <100 mm)	r it latine	(0.0154)	(0.00430)	(0.0154)	(0.002)
Wealth quintiles (ref: Poorest) Poorer (0.0175) (0.00348) (0.0175) (0.00348) Middle 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Middle (0.0107) (0.00219) (0.0107) (0.00219) Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} (0.0111) (0.00225) (0.0112) (0.00224) Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} (0.0123) (0.00245) (0.0123) (0.00245) Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0155) (0.00301) (0.0153) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00377 -0.00343 (0.0120) (0.00238) (0.0120) (0.00238) (0.0120) (0.00238) Climate controlPrecipitation (ref: <100 mm)	Other	-0.0304*	0.00193	-0.0441**	0.00409
Wealth quintiles (ref: Poorest) Poorer 0.0191^* (0.0107) 0.00448^{**} (0.0107) 0.00532^{**} (0.00219) 0.00242^{**} (0.0107) 0.00532^{**} (0.00219) 0.00242^{**} (0.0107) 0.00219 (0.00219) 0.00219 (0.00219) Middle 0.0575^{***} (0.0111) 0.00225 (0.00225) 0.0112 (0.00224) 0.00224 (0.00224) Richer 0.0557^{***} (0.0123) 0.00245 (0.00245) 0.0148^{***} -0.0123 0.00245 (0.00245) Richest 0.0941^{***} (0.0155) 0.00301 (0.0153) 0.00245^{***} 0.00232^{***} Residence (ref: rural) -0.0122 -0.0122 0.000189 -0.00877 -0.000343 (0.0120) 0.00238 (0.0120) Climate control 0.130^{***} (0.0220) $0.00386)$ 0.0220 (0.00388) (0.0220) (0.00331) 0.00607 (0.00322) 200-300 0.148^{***} 0.100 -0.0287^{***} (0.00667) 0.107^{***} $0.00667)0.0025^{***}0.00667)Region X Month\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark\checkmark$		(0.0175)	(0.00348)	(0.0175)	(0.00348)
Poorer 0.0191^* -0.00448^{**} 0.0242^{**} -0.00532^{**} Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} Richest 0.0557^{***} -0.0173^{***} 0.0736^{***} -0.0148^{***} Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 0.0120 (0.0220) (0.00238) (0.0120) (0.00238) Climate control -0.0122^{***} -0.0195^{***} -0.0205^{***} Precipitation (ref: <100 mm)	Wealth quintiles (ref: Poorest)				
Middle (0.0107) (0.00219) (0.0107) (0.00219) Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Richer (0.0111) (0.00225) (0.0112) (0.00224) Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} (0.0123) (0.00245) (0.0123) (0.00245) Richest 0.0941^{***} -0.0173^{***} 0.129^{***} (0.0155) (0.00301) (0.0153) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.00238 (0.0120) (0.00238) (0.0120) (0.0220) (0.00386) (0.0220) (0.00388) $200-300$ 0.148^{***} -0.0242^{***} 0.157^{***} 0.000 0.148^{***} -0.0242^{***} 0.107^{***} 0.000 0.130^{***} -0.0195^{***} $0.0220)$ $0.0331)$ (0.0667) (0.0332) (0.00609) > 300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969) Region X Month \checkmark $<$ \checkmark \checkmark \checkmark	Poorer	0.0191*	-0.00448**	0.0242**	-0.00532**
Middle 0.0575^{***} -0.0105^{***} 0.0676^{***} -0.0121^{***} Richer 0.0557^{***} -0.0109^{***} 0.0736^{***} -0.0148^{***} Richest 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} Richest 0.0941^{***} -0.0123 (0.00245) (0.0123) (0.00245) Residence (ref: rural) -0.0155 (0.00301) (0.0153) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 (0.0120) (0.00238) (0.0120) (0.00238) Climate control 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} $100-200$ 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} (0.0331) (0.00607) (0.0332) (0.00609) >300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969) Region X Month \checkmark \checkmark \checkmark \checkmark Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark		(0.0107)	(0.00219)	(0.0107)	(0.00219)
Richer (0.0111) (0.00225) (0.0112) (0.00224) Richest 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} Richest (0.0123) (0.00245) (0.0123) (0.00245) Residence (ref: rural) 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0155) (0.00301) (0.0153) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 (0.0120) (0.00238) (0.0120) (0.00238) Climate control 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} $100-200$ 0.130^{***} -0.0195^{***} 0.136^{***} -0.0225^{***} (0.0220) (0.0336) (0.0220) (0.00388) $200-300$ 0.148^{***} -0.0242^{***} 0.157^{***} -0.0225^{***} >300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969) >300 $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ Region X Month $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ Region X Month $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$	Middle	0.0575***	-0.0105***	0.0676***	-0.0121***
Richer 0.0557^{***} -0.0119^{***} 0.0736^{***} -0.0148^{***} Richest (0.0123) (0.00245) (0.0123) (0.00245) Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0155) (0.00301) (0.0155) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 (0.0120) (0.02238) (0.0120) (0.00238) Climate control 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} $100-200$ 0.130^{***} -0.0195^{***} 0.136^{***} -0.0225^{***} (0.0220) (0.00386) (0.0220) (0.00388) $200-300$ 0.148^{***} -0.0242^{***} 0.157^{***} $0.0331)$ (0.06677) (0.0332) (0.00609) >300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969)		(0.0111)	(0.00225)	(0.0112)	(0.00224)
Richest (0.0123) (0.00245) (0.0123) (0.00245) Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} (0.0155) (0.00301) (0.0153) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.0122 0.00189 -0.008377 -0.000343 (0.0120) (0.0220) (0.00238) (0.0120) 0.02200 0.130^{***} -0.0195^{***} 0.136^{***} $0.0220)$ (0.0386) (0.0220) (0.00388) $200-300$ 0.148^{***} -0.0242^{***} 0.157^{***} 0.0250^{***} (0.0331) (0.00607) (0.0332) $0.00677)$ (0.00969) (0.0667) (0.00969) >300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969) Region X Month \checkmark \checkmark \checkmark \checkmark Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark	Richer	0.0557***	-0.0119***	0.0736***	-0.0148***
Richest 0.0941^{***} -0.0173^{***} 0.129^{***} -0.0232^{***} Residence (ref: rural) (0.0155) (0.00301) (0.0153) (0.00297) Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 <i>Climate control</i> (0.0120) (0.00238) (0.0120) (0.00238) <i>Climate control</i> (0.0220) (0.0386) (0.0220) (0.00388) 200-300 0.148^{***} -0.0242^{***} 0.157^{***} -0.0255^{***} (0.0331) (0.00607) (0.0332) (0.00609) >300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969) (0.0067) (0.00969) >300 $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ $\sqrt{4}$ Region X Month $\sqrt{4}$ $$	Diless	(0.0123)	(0.00245)	(0.0123)	(0.00245)
(0.0133)(0.0133)(0.0133)(0.0133)(0.0133)(0.0133)Residence (ref: rural) -0.0122 0.000189 -0.00877 -0.000343 (0.0120)(0.0120)(0.00238)(0.0120)(0.00238)Climate control 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} Precipitation (ref: <100 mm) 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} 200-300 0.148^{***} -0.0242^{***} 0.157^{***} -0.0255^{***} (0.0331)(0.00607)(0.0332)(0.00609)> 300 0.100 -0.0287^{***} 0.107 -0.0292^{***} Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark	Richest	0.0941^^^	$-0.01/3^{\circ}$	(0.129^{***})	-0.0232°
Include (ref. 141a) (0.0122) (0.000169) (0.00077) (0.000373) Image: Climate control (0.0120) (0.0120) (0.00238) (0.0120) (0.00238) Precipitation (ref: <100 mm)	Residence (ref. rural)	-0.0133)	0.000180	(0.0155)	(0.00297)
Climate control (0.0120) (0.0120) (0.0120) (0.02120) Precipitation (ref: <100 mm)	Residence (ref. futur)	(0.0122)	(0.00010)	(0.0120)	(0.00238)
Precipitation (ref: <100 mm)	Climate control	(0.0120)	(0.00200)	(0.0120)	(0.00200)
100-200 0.130^{***} -0.0195^{***} 0.136^{***} -0.0205^{***} 200-300 0.148^{***} -0.0242^{***} 0.157^{***} -0.0255^{***} >300 0.148^{***} -0.0242^{***} 0.157^{***} -0.0255^{***} >300 0.100 -0.0287^{***} 0.107 -0.0292^{***} (0.0667) (0.00969) (0.0667) (0.00969) Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark	Precipitation (ref: <100 mm)				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	100-200	0.130***	-0.0195***	0.136***	-0.0205***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0220)	(0.00386)	(0.0220)	(0.00388)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	200-300	0.148***	-0.0242***	0.157***	-0.0255***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0331)	(0.00607)	(0.0332)	(0.00609)
(0.0667) (0.00969) (0.0667) (0.00969) Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark	>300	0.100	-0.0287***	0.107	-0.0292***
Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark		(0.0667)	(0.00969)	(0.0667)	(0.00969)
Region X Year	Pagion V Month	/	/	/	/
	Region X Vear	v	v	v	v
	INGIVII A ITAI	v	v	v	v
Observations 238,253 238,253 238,253 238,253	Observations	238.253	238.253	238.253	238.253
R-squared 0.089 0.068 0.088 0.068	R-squared	0.089	0.068	0.088	0.068

Robust standard errors in parentheses clustered at the EA level

*** p<0.01, ** p<0.05, * p<0.1 Notes: Linear model with high dimensional fixed-effects by Correia (2017). Fixed effects are with respect to the month and year of the interview.

C.8 Varying degrees of heat exposure

	4 m	onths	5 mc	onths	6 m	onths
Dependent variable: WHZ Variables	WHZ (1)	Wasting (2)	WHZ (3)	Wasting (4)	WHZ (5)	Wasting (6)
Heat exposure (>30 °C)	-0.137***	0.0137***	-0.0917***	0.00668*	-0.0422**	-0.000203
	(0.0179)	(0.00317)	(0.0190)	(0.00375)	(0.0214)	(0.00427)
Decision making	0.00290	0.000411	0.00671	-0.000208	0.00894*	-0.000359
	(0.00484)	(0.000861)	(0.00474)	(0.000867)	(0.00465)	(0.000875)
Heat X Decision making	0.00516	-0.00325**	-0.00451	-0.00201	-0.0118	-0.00188
	(0.00761)	(0.00153)	(0.00773)	(0.00160)	(0.00806)	(0.00166)
Child characteristics Maternal characteristics Household characteristics Climate control Region X Month Region X Year	$\begin{array}{c} \checkmark \\ \checkmark \end{array}$	$ \begin{array}{c} \checkmark \\ \checkmark $	$\begin{array}{c} \checkmark \\ \checkmark \end{array}$	$ \begin{array}{c} \checkmark \\ \checkmark $	$\begin{array}{c} \checkmark \\ \checkmark \end{array}$	
Observations	238,253	238,253	238,253	238,253	238,253	238,253
R-squared	0.089	0.068	0.089	0.068	0.088	0.068

Table C.8.1: Effects according	to varying	degrees	of heat exposure
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Robust standard errors in parentheses clustered at the EA level

*** p < 0.01, ** p < 0.05, * p < 0.1*Notes*: Linear model with high dimensional fixed-effects by Correia (2017). Fixed effects are with respect to the month and year of the interview.

UQR - Bootstrap standard errors **C.9**

Table C.9.1: Results from UQR with bootstrap standard errors

Dana dan tana dalam MILIZ	010	050	000
Dependent variable: WHZ	Q10 (1)	Q50	Q90
Variables	(1)	(2)	(3)
Heat exposure (>30 °C)	-0.0608*	-0.140***	-0.173***
	(0.0327)	(0.0190)	(0.0303)
Decision making	-0.0105	0.00113	0.00147
	(0.00883)	(0.00557)	(0.00959)
Heat exposure X Decision making	0.0402***	0.00431	-0.00736
Child sharestaristics	(0.0151)	(0.00769)	(0.0123)
Child's and (months)	0.0104***	0.00050***	0.0119***
Child's age (monuls)	(0.0194)	(0.00356)	-0.0113
Child's say (raf: famala)	(0.000317)	0.00161	0.0650***
Child's Sex (Tel: Telliale)	-0.133	(0.00101)	(0.0039)
Birth order (count)	0.0620***	0.0624***	(0.0102) 0.124***
bitti older (count)	(0.002)	(0.0027)	(0.127)
Maternal characteristics	(0.0141)	(0.00700)	(0.0121)
Mother's age (years)	-0.00146	-0.000384	-0 000774
mother's age (Jears)	(0.00103)	(0.000499)	(0.000804)
Mother's height (cm)	0.00557***	0.00480***	0.00451***
(int)	(0.00114)	(0.000550)	(0.000892)
Mother's education (years)	0.0209***	0.0100***	0.00835***
inotitor o culturion (jouro)	(0.00221)	(0.00115)	(0.00185)
Household characteristics	(0.00221)	(0.00110)	(0.00100)
Number of children under five (count)	-0.0155**	-0.0208***	-0.0417***
	(0.00763)	(0.00357)	(0.00554)
Sex of household head (ref: female)	0.00911	0.0253**	0.00887
	(0.0188)	(0.0105)	(0.0166)
Source of drinking water (ref: Piped)			
Well	-0.0144	-0.0183*	-0.0184
	(0.0208)	(0.0108)	(0.0175)
Other	0.0120	0.0153	0.0168
	(0.0231)	(0.0124)	(0.0202)
Sanitation type (ref: Flush)			
Pit latrine	0.0478	-0.00363	-0.0401
	(0.0314)	(0.0161)	(0.0254)
Other	-0.0152	-0.0267	-0.0301
	(0.0357)	(0.0183)	(0.0286)
Wealth quintiles (ref: Poorest)			
Poorer	0.0447**	0.0188*	0.000695
	(0.0225)	(0.0107)	(0.0169)
Middle	0.106***	0.0577***	0.0322*
	(0.0230)	(0.0113)	(0.0182)
Richer	0.122***	0.0528***	0.0131
P (1)	(0.0252)	(0.0128)	(0.0202)
Richest	0.176***	0.0809***	0.0/29***
	(0.0309)	(0.0166)	(0.0267)
Residence (ref: rural)	-0.0014/	-0.00190	-0.00695
Climate control	(0.0244)	(0.0117)	(0.0191)
Droginitation (rof: <100 mm)			
100-200	0 200***	0 195***	0.0804**
100-200	(0.209	(0.123	(0.0367)
200-300	0.258***	0 137***	0.0680
200-300	(0.0629)	(0.0357)	(0,0560)
>300	0.304***	0.0464	-0.0488
	(0.0995)	(0.0759)	(0.128)
	(0.0770)	(0.0707)	(0.120)
Region X Month	\checkmark	\checkmark	\checkmark
Region X Year	, ,	, ,	· ✓
0			
Observations	238,253	238,253	238,253
R-squared	0.069	0.071	0.041

Bootstrap standard errors (50 replications) in parentheses clustered at the EA level *** p < 0.01, ** p < 0.05, * p < 0.1*Notes*: Unconditional quantile regression with high dimensional fixed-effects by (Rios-Avila, 2020). Fixed effects are with respect to the month and year of the interview.

C.10 UQR - Quantiles 25 and 75

Table C.10.1: Rest	ilts from UQR	for quantile	es 25 and 75
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Dependent variable: WHZ Q25 Q75 Variables (1) (2) Heat exposure (>30 °C) -0.120*** -0.144*** Decision making 0.00898 0.00623 Decision making 0.00898 0.00862 Heat exposure X Decision making 0.00898 -0.00335*** Child's age (months) 0.0115*** 0.000320 Child's sex (ref: female) -0.632*** 0.00339*** Child's sex (ref: female) -0.0632*** 0.00755 Mother's age (years) -0.0105* 4.39e-05 (0.000619) (0.000619) (0.000619) Mother's height (cm) 0.0153*** 0.00428** Number of children under five (court) -0.0185*** 0.00220*** Number of children under five (court) -0.0185*** -0.0272*** Number of children under five (court) -0.0185** 0.0208* Sex of household head (ref: female) 0.0239 0.0165 Source of drinking water (ref: Piped) Well -0.0186 -0.022 Well -0.0239 0.0165			
Variables (1) (2) Heat exposure (>30 °C) -0.120**** -0.144**** (0.0217) (0.0208) Decision making 0.00889 -0.00662 (0.00423) (0.00653) Heat exposure X Decision making 0.00898 -0.00862 (0.00433) (0.00856) Child's age (months) 0.0015*** -0.00335*** Child's age (months) 0.00755) (0.00622) 0.006622 Birth order (count) 0.00755) (0.00675) 0.006622 Birth order (count) 0.00755) (0.00657) 0.000547* Mother's age (years) -0.0105* 4.39e-05 Mother's height (cm) 0.00511*** 0.000657) Mother's education (years) 0.0115**** -0.0272*** Number of children under five (count) -0.0177 (0.00145) Sex of household head (ref: female) -0.0278 -0.0272*** Number of children under five (count) -0.0278 -0.0278 Outer -0.0278 -0.0278 Sex of household head (ref: female) 0.0286	Dependent variable: WHZ	Q25	Q75
Heat exposure (>30 °C) -0.120*** -0.144*** Decision making 0.0089 0.00623 Heat exposure X Decision making 0.00898 0.006623 Ghild characteristics 0.00898 0.006623 Child's age (months) 0.0115*** -0.00335*** Child's age (months) 0.0115*** -0.0032*** Child's age (months) 0.0729*** 0.0755 Child's age (months) 0.0105* 4.39e-05 Child's age (years) -0.00105* 4.39e-05 Mother's age (years) -0.00105* 4.39e-05 Mother's education (years) 0.0153*** 0.000615) Mother's education (years) 0.0153*** 0.0022*** Number of children under five (count) -0.0185*** -0.0272*** Number of children under five (count	Variables	(1)	(2)
Heat exposure (>30 °C) 0.120*** 0.120*** 0.00289 Decision making 0.00889 0.00623 Heat exposure X Decision making 0.00898 0.00856 Heat exposure X Decision making 0.00898 0.00856 Child characteristics 0.000320 0.000320 Child's age (months) 0.0115*** 0.00335*** Child's sex (ref: female) -0.0632** 0.0393*** Child's sex (ref: female) -0.0605** 0.0393*** Mother's age (years) -0.0105* 4.39e-05 Maternal characteristics 0.000517* 0.000615* Mother's height (cm) 0.0115**** 0.000517* Mother's education (years) 0.0115**** 0.00015* Sex of household head (ref: female) 0.0208* 0.00445 Number of children under five (count) 0.0115* 0.0217** Other 0.0208* 0.0165 0.0165 Sex of household head (ref: female) 0.0208* 0.0217** Other 0.0239 0.0165 0.0165 Other 0.0272***		(1)	(=)
Heat exposure (>30 °C) -0.120*** -0.144*** 0.00217) (0.0208) Decision making 0.00889 0.00623 Decision making 0.00898 -0.00323 Heat exposure X Decision making 0.00898 -0.00335*** Outld's age (months) 0.0115*** 0.000230 Child's age (months) -0.0632*** 0.000288) Child's sex (ref: female) -0.0632*** 0.000755 Maternal characteristics 0.000755 4.39e-05 Mother's age (years) 0.00115** 0.000515) Mother's deucation (years) 0.0115*** 0.000280*** Mouber of children under five (count) 0.0152*** 0.00028* Mouber of children under five (count) -0.0185*** -0.0272*** Number of children under five (count) -0.0185*** -0.0272*** Number of children under five (count) -0.0185 -0.0272*** Vell -0.0017* (0.0130) Sex of household head (ref: female) 0.00434 -0.01615 Sunitation type (ref: Flush) -1111 0.0186			
Interpreter (CFL) (0.0217) (0.0208) Decision making 0.00889 0.00623 Heat exposure X Decision making 0.00898 -0.00862 (0.0042) (0.00653) Heat exposure X Decision making 0.00898 -0.00335*** Child characteristics (0.000220) (0.000220) Child's age (months) 0.0115*** -0.00335*** Child's sex (ref: female) -0.0632*** 0.0393*** (0.00755) (0.00622) Birth order (count) 0.0755 Maternal characteristics (0.00057) (0.000617) Mother's height (cm) 0.00531*** 0.00428*** (0.00057) (0.000617) (0.000617) Mother's height (cm) 0.0155*** 0.00428*** (0.00138) (0.00129) Household characteristics Number of children under five (count) -0.0185*** -0.0272*** Number of children under five (count) -0.0185 -0.0248** (0.00138) (0.0117) Source of drinking water (ref: Piped) Well -0.0278 -0.0202 Well	Heat exposure (>30 $^{\circ}$ C)	-0.120***	-0.144***
$\begin{array}{ccccc} (0.0217) & (0.0230) \\ (0.00889 & 0.00623 \\ (0.00943) & (0.00835 \\ (0.00943) & (0.00835 \\ (0.00943) & (0.00835 \\ (0.000320) & (0.000335^{***} \\ (0.000320) & (0.000335 \\ (0.000320) & (0.000320) \\ (0.000320) & (0.000320) \\ (0.000320) & (0.000288 \\ (0.000755) & (0.00692) \\ Birth order (count) & 0.0729^{***} & (0.0754^{****} \\ (0.00726) & (0.00855) \\ \end{tabular} \begin{tabular}{lllllllllllllllllllllllllllllllllll$		(0.0217)	(0.0208)
Decision making 0.00632) 0.00623) (0.00612) (0.00653) Heat exposure X Decision making 0.00898 -0.00862 Child characteristics 0.0115*** -0.00335*** Child's age (months) 0.0115*** -0.00335*** Child's sex (ref: female) -0.022*** 0.00755) (0.00659) Birth order (count) 0.0729*** 0.0754*** (0.000519) Mother's age (years) -0.0105* 4.39e-05 (0.000619) (0.000517) Mother's height (cm) 0.00531*** 0.00820*** (0.000512) Mother's education (years) 0.0153*** 0.00820*** (0.000451) Mumber of children under five (count) -0.0185** -0.0272*** Number of children under five (count) -0.0185** -0.0272*** Number of children under five (count) -0.0133 (0.0117) Source of drinking water (ref: Piped) -0.02239 0.0165 Well -0.02239 0.0165 Other -0.0278 -0.0367* Other 0.0238** 0.00975 <	Desision moltine	0.0217)	0.0200)
(0.00612) (0.00633) Heat exposure X Decision making 0.00898 -0.00862 (0.00943) (0.00856) (0.00943) Child's age (months) 0.0115^{+++} (0.000320) Child's sex (ref: female) -0.632^{+++} (0.00755) (0.00755) (0.00692) Birth order (count) 0.0729^{+++} (0.07555) Maternal characteristics (0.00679) (0.000679) Mother's age (years) -0.00105^{+} $4.39e-05$ (0.00679) (0.000679) (0.000679) Mother's education (years) 0.0153^{+++} 0.00820^{+++} (0.000679) (0.000679) (0.000679) Mother's education (years) 0.0153^{+++} 0.0028^{+++} (0.00138) (0.00129) Household head (ref: female) 0.0185^{+++} Number of children under five (count) -0.0185^{+++} -0.0272^{+++} Number of ching water (ref: Piped) $Well$ -0.00434 -0.0161 Well 0.00434 -0.0161 (0.0117) Source of drinking water (ref: Piped) $Well$ -0.0278 -0.0367^{+} Wealth quintiles (ref: Poorest) $Well$ 0.0388^{++} 0.00975 Poorer 0.0388^{++} 0.00979^{+++} 0.0229^{+++} $Nother's ender (ref: rural)$ 0.0166^{+++} 0.0228^{+++} $Mother's age (ref: Piorest)$ $Well$ 0.0138^{+++} 0.0027^{+++} $Mother's (ref: rural)$ 0.0166^{++++} 0.0229^{++++} $Nother's$ (0.0123) (0.1177) <td>Decision making</td> <td>0.00889</td> <td>0.00623</td>	Decision making	0.00889	0.00623
Heat exposure X Decision making 0.00898 -0.00862 Child characteristics 0.00943 0.00356 Child's age (months) 0.0115*** 0.003220 0.003288) Child's sex (ref: female) -0.0632*** 0.00393*** 0.00393*** Child's sex (ref: female) 0.0729*** 0.0754*** 0.00395*** Maternal characteristics (0.000619) (0.000517) Mother's age (years) -0.00105* 4.39e-05 Mother's height (cm) 0.00531*** 0.00428*** (0.000679) (0.00057) Mother's education (years) 0.0115*** 0.00428*** (0.00138) (0.00128) (0.00128) Mumber of children under five (count) -0.0115*** -0.0272*** (0.00445) (0.00386) 0.0208* 0.0248** (0.0125) (0.0117) 0.0208* 0.0248** (0.0123) (0.0117) 0.0228* 0.02129 Mother's education (years) -0.0248** (0.0133) Sex of household head (ref: female) -0.0278 -0.0276 Se		(0.00612)	(0.00653)
Child characteristics (0.00943) (0.00856) Child's age (months) 0.0115^{+**} 0.00335^{+**} Child's sex (ref: female) -0.0632^{+**} 0.0393^{+**} Child's sex (ref: female) -0.0632^{+**} 0.0393^{+**} Distribution of the second of th	Heat exposure X Decision making	0.00898	-0.00862
Child characteristics Child's age (months) Child's (0.00320) Child's (0.000320) Child's age (months) 0.0115*** 0.00332** 0.000288) Child's sex (ref: female) -0.0632*** 0.0333*** 0.000288) Child's sex (ref: female) -0.0632*** 0.0393*** 0.000692) Birth order (count) 0.0729*** 0.0754*** 0.000619) Mother's age (years) -0.00105* 4.39e-05 0.0000619) Mother's height (cm) 0.00531*** 0.00820*** 0.000129) Mother's education (years) 0.0153*** 0.00820*** 0.000428*** Number of children under five (count) -0.0272*** 0.0028* 0.0221*** Number of children under five (count) -0.0278** -0.0272*** 0.00136) Sex of household head (ref: female) 0.0208* 0.0248** 0.00147) Well -0.0147 (0.0147) 0.01147) Well -0.0278 -0.0278 -0.0367* Well (0.0138) (0.01147) 0.0329*** Wealth quintiles (ref: Poorest) Poor		(0.00943)	(0.00856)
Child's age (months) 0.0115^{***} 0.00335^{***} Child's sex (ref: female) 0.0632^{***} 0.0393^{***} Child's sex (ref: female) 0.0755 (0.00622) Birth order (count) 0.0729^{***} 0.0754^{***} Maternal characteristics (0.000679) (0.000679) Mother's neight (cm) 0.00571 (0.000679) Mother's education (years) 0.0153^{***} 0.000679 Mother's education (years) 0.0153^{***} 0.0022^{***} Mother's education (years) 0.0153^{***} 0.0020^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} Number of children under five (count) -0.0125 (0.01125) Source of drinking water (ref: Piped) Well (0.0133) (0.0117) Well 0.0125 (0.0176) (0.0133) (0.0176) Other 0.0239 0.0165 (0.0177) (0.0186) Sanitation type (ref: Flush) Pit latrine 0.0186 0.0223 (0.0176) Other 0.0338	Child characteristics	(,	()
Child's age (months) $0.00135^{-0.003320}$ $0.000320^{-0.00335}$ Child's sex (ref: female) $0.000320^{-0.000525}$ $0.000622^{-0.00555}$ Birth order (count) 0.0729^{+++} $0.00755^{-0.00555}$ Mother's age (years) -0.00105^{*} $4.39e.05$ Mother's age (years) -0.00105^{*} $4.39e.05$ Mother's height (cm) 0.00531^{+++} $0.000619^{-0.000615}$ Mother's education (years) 0.0138^{*++} 0.000622^{*++} Mumber of children under five (count) -0.0138^{*++} 0.00228^{*++} Number of children under five (count) -0.0185^{*+-} -0.0272^{*++} Number of children under five (count) -0.0185^{*+-} -0.0272^{*++} Source of drinking water (ref: Piped) $Well$ -0.00434^{-} -0.0161^{-} Well -0.0186^{-} 0.0202^{-} 0.0136^{-} 0.0176^{-} Other 0.0278^{*} 0.0329^{*++} 0.0329^{*++} 0.0329^{*++} Poir 0.0133^{*} 0.0176^{-} 0.0223^{*} 0.0176^{-} Outr 0.0165^{*} 0.0297^{*+} 0.0329^{*++} 0.0329^{*++}	Child's age (months)	0.0115***	0 00005***
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Child's age (monuls)	0.0115	-0.00335***
Child's sex (ref: female) -0.0632*** 0.0393*** Birth order (count) (0.00755) (0.00692) Birth order (count) 0.0729*** 0.0754*** Maternal characteristics - - Mother's age (years) -0.00105* 4.39e-05 (0.000619) (0.000547) 0.00428*** Mother's height (cm) 0.0531*** 0.00428*** (0.00153) 0.0153*** 0.00820*** Mother's education (years) 0.0153*** -0.0272*** (0.00455) (0.00386) -0.0272*** Number of children under five (count) -0.0185*** -0.0272*** (0.0125) (0.0117) Source of drinking water (ref: Piped) -0.0239 0.0165 Well -0.0186 -0.0202 (0.0197) Other -0.0278 -0.0367* Other -0.0278 -0.0367* Other -0.0278 -0.0272 Well -0.0161 (0.0117) Other -0.0278 -0.0367* Other -0.0278 -0.0367* Other 0.0186 -0.0278		(0.000320)	(0.000288)
Birth order (count) (0.00755) (0.00692) Birth order (count) 0.0729^{***} 0.0754^{***} Maternal characteristics (0.000619) (0.000547) Mother's age (years) -0.00105^* $4.39e.05$ (0.000679) (0.000679) (0.000615) Mother's height (cm) 0.00531^{***} 0.00820^{***} (0.000679) (0.000679) (0.000615) Mother's education (years) 0.0153^{***} 0.00820^{***} (0.000679) (0.000128) 0.00820^{***} Household characteristics 0.0185^{***} -0.0272^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} (0.00445) (0.00386) 0.0248^{**} (0.00445) (0.00386) 0.0248^{**} (0.0125) (0.0117) Source of drinking water (ref: Piped) $Well$ -0.0278 (0.0147) (0.0136) $0.0117)$ Sanitation type (ref: Flush) Wil 0.0138^{**} $Pit latrine$ 0.0186 -0.0202 (0.0197) (0.0176) $Other$ 0.0338^{**} 0.00975 (0.0134) (0.0117) Middle 0.0991^{***} 0.0229^{***} $Porer$ (0.0138) (0.0123) $Richert$ 0.0155 (0.0140) (0.0155) (0.0140) (0.0155) (0.0140) (0.0126) (0.0123) $Richert$ 0.0297^{**} (0.0126) (0.0248) (0.0126) (0.0248) </td <td>Child's sex (ref: female)</td> <td>-0.0632***</td> <td>0.0393***</td>	Child's sex (ref: female)	-0.0632***	0.0393***
Birth order (count) 0.0729^{***} 0.0754^{****} Maternal characteristics		(0.00755)	(0.00692)
bit if otder (count) 0.0292 0.0947 Maternal characteristics 0.00926 (0.00855) Maternal characteristics 0.000619 (0.000547) Mother's height (cm) 0.00531^{**} 0.00428^{**} (0.00679) (0.000619) (0.000619) Mother's education (years) 0.0153^{***} 0.00820^{***} Number of children under five (count) 0.0185^{***} 0.0272^{***} Number of children under five (count) 0.0185^{***} 0.0272^{***} (0.00445) (0.00386) 0.0248^{**} (0.0125) (0.0117) Source of drinking water (ref: Piped) 0.0239 0.0165 Well -0.0434 -0.0161 (0.0133) (0.0119) Other 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) Pit Pit (0.0134) (0.0117) Middle 0.038^{**} 0.00975 (0.0138) (0.0123) Wealth quintiles (ref: Poorest) $Poorer$ 0.0388^{**} 0.00975 Poorer 0.03891^{***} 0.0297^{**}	Birth order (count)	0 0720***	0.0754***
Maternal characteristics (0.00926) (0.00053) Mother's age (years) -0.00105^* $4.39e-05$ (0.000619) (0.000547) (0.000547) Mother's height (cm) 0.00531^{***} 0.00428^{***} (0.000679) (0.000615) (0.000679) Mother's education (years) 0.0153^{***} 0.00820^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} (0.00445) (0.00386) (0.0117) Source of drinking water (ref: Piped) (0.0125) (0.0117) Well -0.00434 -0.0161 (0.0133) (0.0119) (0.0133) Other 0.0239 0.0165 Sanitation type (ref: Flush) -0.0176 (0.0223) Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) (0.0177) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) (0.0117) Middle 0.0919^{***} 0.0227^{**} (0.0138) (0.0123) (0.0140) Richest 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) (0.0140) Richest 0.0613^{***} (0.0128) Climate control -0.0176 0.0223 Precipitation (ref: <100 mm)	Birtir order (count)	(0,0000()	(0,00055)
Maternal characteristics -0.00105* 4.39e-05 Mother's age (years) -0.00105* 4.39e-05 Mother's height (cm) 0.00531*** 0.00428*** Mother's education (years) 0.0153*** 0.000820*** Mother's education (years) 0.0185*** -0.0272*** Number of children under five (count) -0.0185*** -0.0272*** Number of children under five (count) -0.0185*** -0.0248** (0.00445) (0.00386) Sex of household head (ref: female) 0.0208* 0.0248** (0.0125) (0.0117) Source of drinking water (ref: Piped) - - - Well -0.0186 -0.0202 (0.0133) (0.0119) Other 0.0223 (0.0176) Other Porer 0.0338** 0.00975 (0.0134) (0.0123) Middle 0.0185 (0.0123) (0.0123) Wealth quintiles (ref: Poorest) - 0.0227** (0.0138) Poorer 0.03891*** 0.0297** (0.0140) Richest 0.0365**		(0.00926)	(0.00855)
Mother's age (years) -0.00105^* $4.39e.05$ Mother's height (cm) 0.00531^{***} 0.000547) Mother's education (years) 0.0153^{***} 0.00820^{***} Mother's education (years) 0.0153^{***} 0.00820^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} Source of drinking water (ref: Piped) 0.0208^* 0.0248^{***} Well -0.00434 -0.0161 (0.01147) (0.0130) (0.0117) Source of drinking water (ref: Piped) 0.0239 0.0165 Well -0.0278 -0.0367^* (0.0197) (0.0176) 0.0170 Other 0.0338^{**} 0.00975^* 0.0223 (0.0177) 0.0329^{***} Poorer 0.0338^{**} 0.0329^{***} Poorer 0.0338^{**} 0.0297^{**} Middle 0.0165 (0.0140) Richer 0.136^{***} 0.0297^{**} <tr< td=""><td>Maternal characteristics</td><td></td><td></td></tr<>	Maternal characteristics		
Mother's height (cm) (0.000619) (0.000547) Mother's education (years) 0.0153^{***} 0.00428^{***} Mother's education (years) 0.0153^{***} 0.00820^{***} Number of children under five (count) -0.185^{***} -0.0272^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} (0.00445) (0.00386) 0.0248^{**} (0.00125) (0.0117) 0.0248^{**} Source of drinking water (ref: Piped) 0.0238^{*} (0.0119) Well -0.00434^{*} -0.0161^{*} (0.0147) (0.0133) $(0.0119)^{*}$ Other 0.0223^{*} $(0.0147)^{*}$ Pit latrine 0.0186^{*} -0.0202^{*} Porer $(0.0134)^{*}$ $(0.0176)^{*}$ Porer 0.0338^{**} 0.00975^{*} (0.0134) $(0.0117)^{*}$ Middle 0.0919^{***} 0.0329^{***} (0.0134) $(0.0117)^{*}$ Middle 0.0919^{***} 0.0227^{**} (0.0138) $(0.0123)^{*}$ Richer 0.0891^{***} 0.0227^{***} (0.0140) $(0.0140)^{**}$ Richest 0.136^{***} 0.0603^{***} (0.0146) $(0.0140)^{**}$ $(0.0140)^{**}$ Residence (ref: rural) -0.166^{***} 0.109^{***} $100-200$ 0.166^{***} 0.109^{***} 0.0201 0.0248^{***} $(0.0248)^{*}$ $200-300$ 0.221^{***} 0.131^{***} 0.030^{*} 0.221^{***} $0.03846)^{*}$	Mother's age (years)	-0.00105*	4.39e-05
Mother's height (cm) 0.00531^{+++} 0.00428^{+++} Mother's education (years) 0.0153^{++++} 0.00820^{++++} Mumber of children under five (count) -0.0185^{++++} -0.0272^{++++} Number of children under five (count) -0.0185^{++++} -0.0272^{++++} Number of children under five (count) -0.0185^{++++} -0.0272^{++++} Number of children under five (count) -0.0185^{++++} -0.0272^{++++} Sex of household head (ref: female) 0.00434 -0.0161 Source of drinking water (ref: Piped) -0.00434 -0.0165 Well -0.00434 -0.0165 0.0147 (0.0130) (0.0117) Sanitation type (ref: Flush) -1.0278 -0.0202 Porer 0.0388^{++} 0.00975 (0.0123) (0.0117) Middle 0.0975 (0.0138) (0.0117) Middle 0.0328^{+++} $Poorer$ 0.0338^{+++} 0.0138 (0.0123) Richer 0.368^{++++} 0.0165 <td></td> <td>(0.000619)</td> <td>(0.000547)</td>		(0.000619)	(0.000547)
Module1's neight (Lift) 0.0031^{-1} 0.00423^{-1} Mother's education (years) 0.0153^{+**} 0.000615) Mother's education (years) 0.0185^{+**} 0.0022^{+**} Number of children under five (count) -0.0185^{+**} -0.0272^{+**} Number of children under five (count) -0.0185^{+**} -0.0272^{+**} (0.00445) (0.00386) 0.0248^{**} (0.0125) Source of drinking water (ref: Piped) 0.0239 0.0165 (0.0117) Source of drinking water (ref: Flush) 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) $-0.0278^{-0.0367^{*}}$ (0.0223) (0.0176) Other 0.0238^{**} 0.0329^{***} $(0.0386)^{**}$ Wealth quintiles (ref: Poorest) -0.0278^{***} 0.0329^{***} Poorer 0.0388^{**} 0.00975^{**} 0.0297^{**} Middle 0.0919^{***} 0.0297^{**} 0.0229^{***} Middle 0.0919^{***} 0.0297^{**} 0.0297^{**} Richer 0.0381^{**} 0.0297^{**} 0.0207^{**} 0.0283 <	Mothor's height (cm)	0.00521***	0.00428***
$\begin{array}{ccccccc} (0.000679) & (0.000615) \\ 0.0153^{***} & 0.00820^{***} \\ (0.00138) & (0.00129) \\ \hline \\ \begin{array}{c} \mbox{Household characteristics} \\ \mbox{Number of children under five (count) } & -0.0185^{***} & -0.0272^{***} \\ (0.00445) & (0.00386) \\ \mbox{Sex of household head (ref: female) } & 0.0208^{*} & 0.0248^{**} \\ (0.0125) & (0.0117) \\ \mbox{Source of drinking water (ref: Piped) } \\ \mbox{Well} & -0.00434 & -0.0161 \\ (0.0133) & (0.0119) \\ \mbox{Other} & 0.0239 & 0.0165 \\ (0.0147) & (0.0136) \\ \mbox{Sanitation type (ref: Flush) } \\ \mbox{Pit latrine} & 0.0186 & -0.0202 \\ (0.0197) & (0.0176) \\ \mbox{Other} & -0.0278 & -0.0367^{*} \\ (0.0223) & (0.0198) \\ \mbox{Wealth quintiles (ref: Poorest) } \\ \mbox{Poorer} & 0.0338^{**} & 0.00975 \\ (0.0138) & (0.0123) \\ \mbox{Middle} & 0.0919^{***} & 0.0329^{***} \\ (0.0138) & (0.0123) \\ \mbox{Richer} & 0.0381^{***} & 0.0297^{**} \\ (0.0138) & (0.0123) \\ \mbox{Richer} & 0.0381^{***} & 0.0297^{**} \\ (0.0138) & (0.0123) \\ \mbox{Richer} & 0.0381^{***} & 0.0297^{**} \\ (0.0136) & (0.0128) \\ \mbox{Climate control} \\ \mbox{Precipitation (ref: <100 mm) } \\ Precipit$	model o height (CIII)	0.00001	(0.000(15)
Mother's education (years) 0.0153^{***} 0.00820^{***} Household characteristics (0.00138) (0.00129) Household characteristics -0.0185^{***} -0.0272^{***} Number of children under five (count) -0.0185^{***} -0.0272^{***} (0.00445) (0.00386) 0.0248^{**} (0.0125) (0.0117) Source of drinking water (ref: Piped) -0.00434 -0.0161 Well -0.00434 -0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) Pit latrine 0.0186 -0.0202 (0.0177) (0.0176) 0.0176 Other -0.0278 -0.0367^* (0.0123) (0.0117) 0.0329^{***} Poorer 0.0338^{**} 0.00975 (0.0138) (0.0123) (0.0123) Richer 0.03891^{***} 0.0297^{**} (0.0184) (0.0128) (0.0140) (0.0128) Climate control (0.0165^{***}) (0.0248) (0.0248)		(0.0006/9)	(0.000615)
(0.00138)(0.00129)Household characteristicsNumber of children under five (count) -0.0185^{***} -0.0272^{***} Sex of household head (ref: female) 0.0208^* 0.0248^{**} Source of drinking water (ref: Piped)Well -0.00434 -0.0161 Well -0.00434 -0.0161 (0.0133) (0.0119) Other 0.0229 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) Pit latrine 0.0186 -0.0202 Other 0.0278 -0.0367^* (0.0127) (0.0176) Other 0.0278 -0.0367^* (0.0123) (0.0198) Wealth quintiles (ref: Poorest) $Poorer$ 0.0338^{**} 0.00975 Poorer 0.0338^{**} 0.00297^{**} (0.0138) (0.0123) Middle 0.0919^{***} 0.0229^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0128) Climate control $(0.0166^{***}$ 0.109^{***} (0.0283) Precipitation (ref: <100 mm)	Mother's education (years)	0.0153***	0.00820***
Household characteristics -0.0185*** -0.0272*** Number of children under five (count) -0.0185*** (0.00386) Sex of household head (ref: female) 0.0208* 0.0248** Source of drinking water (ref: Piped) (0.0125) (0.0117) Source of drinking water (ref: Piped) -0.00434 -0.0161 Well -0.0239 0.0165 Other 0.0239 0.0165 Sanitation type (ref: Flush) -0.0186 -0.0202 Pit latrine 0.0186 -0.0202 Other -0.0278 -0.0367* Other -0.0278 -0.0367* Poorer 0.0338** 0.00975 Poorer 0.0338** 0.00975 Middle 0.0919*** 0.0329*** Nichest 0.136* 0.0603*** Nichest 0.136*** 0.0603*** Nichest 0.0155) (0.0140) Richest 0.0166*** 0.109*** 0.0200 0.166*** 0.109*** 0.0201 0.02483 0.0770 0.0300 0.221*** 0.131***		(0.00138)	(0.00129)
Number of children under five (count) -0.0185^{***} -0.0272^{***} Number of children under five (count) -0.0185^{****} (0.00386) Sex of household head (ref: female) 0.0208^* 0.0248^{**} Source of drinking water (ref: Piped) well -0.00434 -0.0161 Well -0.00434 -0.0161 (0.0133) (0.0117) Other 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) Pit latrine 0.0186 -0.0202 (0.0197) Other -0.0278 -0.0367^* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) $Poorer$ 0.0338^{**} 0.00975 Poorer 0.0338^{**} 0.00975 (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0123) Residence (ref: rural) -0.0176 0.0283 (0.0140) Nichest 0.0166^{***} 0.109^{***} (0.0248) 200.300 0.221^{***} 0.131^{***} 2	Household characteristics	(、·····
Number of children under nee (count) -0.00133 -0.0228^{**} Sex of household head (ref: female) 0.0208^* (0.00445) (0.00386) Source of drinking water (ref: Piped) 0.0208^* (0.0117) Well -0.00434 -0.0161 (0.0133) (0.0119) Other 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) (0.0147) (0.0176) (0.0123) (0.0176) Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) Other 0.038^{**} 0.00975 (0.0223) (0.0198) Wealth quintiles (ref: Poorest) 0.038^{***} 0.00975 Poorer 0.0381^{***} 0.0297^{***} Middle 0.0919^{***} 0.0297^{***} (0.0155) (0.0140) (0.0123) Richer 0.03891^{***} 0.0603^{***} (0.0196) (0.0184) (0.0123) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) (0.0146) Climate control (0.0261) (0.0248) $200-300$ 0.166^{***} 0.109^{***} 2300 0.143^* 0.0770 $0.0846)$ $\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{$	Number of shildren under five (sount)	0.0105***	0 0070***
(0.00445) (0.00386) Sex of household head (ref: female) 0.0208^* 0.0248^{**} Source of drinking water (ref: Piped) (0.0125) (0.0117) Well -0.00434 -0.0161 (0.0133) Other 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) (0.0197) (0.0176) Other -0.0278 -0.0367^* (0.0223) (0.0197) (0.0176) Other -0.0278 -0.0367^* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) -0.0338^{**} Poorer 0.0338^{**} 0.00975 (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0146) (0.0184) Residence (ref: rural) -0.0176 0.02283 (0.0146) (0.0128) Climate control -0.0176 0.0283 Precipitation (ref: <100 mm)	Number of children under live (count)	-0.0185	-0.02/2***
Sex of household head (ref: female) 0.0208^* 0.0248^{**} Source of drinking water (ref: Piped) (0.01125) (0.0117) Source of drinking water (ref: Piped) (0.0133) (0.0117) Well -0.00434 -0.0161 (0.0133) (0.0119) Other 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) " Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) Other -0.0278 -0.0367^* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) " " Poorer 0.0338^{**} 0.00975 Middle 0.0919^{***} 0.0329^{***} 0.0134) (0.01123) Richer 0.0891^{***} 0.0297^{**} 0.0176 0.00283 (0.0140) (0.0128) Climate control " " (0.0146) (0.0128) Precipitation (ref: <100 mm)		(0.00445)	(0.00386)
(0.0125)(0.0117)Source of drinking water (ref: Piped)Well -0.00434 -0.0161 (0.0133)(0.0119)Other 0.0239 0.0165 (0.0147)(0.0136)Sanitation type (ref: Flush) (0.0147) (0.0176)Pit latrine 0.0186 -0.0202 (0.0197)(0.0176)Other -0.0278 $-0.0367*$ Poorer(0.0134)(0.0117)Middle $0.0919***$ $0.0329***$ (0.0138)(0.0123)(0.0123)Richer $0.0891***$ $0.0297**$ (0.0155)(0.0140)(0.0123)Richest $0.136***$ $0.0603***$ (0.0196)(0.0184)(0.0140)Residence (ref: rural) -0.0176 0.02283 (0.0261)(0.0248)(0.0261)(0.0248)200-300 $0.221***$ $0.131***$ 0.020 0.146^*** 0.0770 0.0773 (0.0846) $\sqrt{\checkmark$ Precipitation (ref: <100 mm)	Sex of household head (ref: female)	0.0208*	0.0248**
Source of drinking water (ref: Piped) $(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,$		(0.0125)	(0.0117)
Well -0.00434 -0.0161 Well 0.0133) (0.0119) Other 0.0239 0.0165 (0.0147) (0.0136) Sanitation type (ref: Flush) (0.0197) (0.0176) Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) (0.0197) Other -0.0278 -0.0367* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) Poorer 0.0338** 0.00975 (0.0138) (0.0117) Middle Middle 0.0919*** 0.0229*** (0.0138) (0.0123) Richer Nicher 0.0891*** 0.0297** (0.0155) (0.0140) Residence (ref: rural) -0.0176 0.00283 (0.0196) (0.0184) (0.0128) Climate control 0.021*** 0.0131 Precipitation (ref: <100 mm)	Source of drinking water (ref. Piped)		
Wein -0.00434 -0.0161 (0.0133)Other (0.0133) (0.0119) $(0.0136)Sanitation type (ref: Flush)(0.0147)(0.0136)Pit latrine0.0186-0.0202(0.0197)(0.0176)(0.0176)Other0.0223-0.0367*(0.0223)(0.0198)Wealth quintiles (ref: Poorest)Poorer0.0338^{**}0.00975(0.0134)Poorer0.0338^{**}0.00975(0.0134)(0.0117)Middle0.0919^{***}0.0329^{***}(0.0138)(0.0123)Richer0.0891^{***}0.0227^{**}(0.0155)(0.0140)Richest0.136^{***}0.0603^{***}(0.0155)(0.0144)(0.0128)Climate controlPrecipitation (ref: <100 mm)100-2000.166^{***}0.109^{***}(0.0261)(0.0248)200-300200-3000.21^{***}0.0382)0.0340>3000.143^{*}0.0770(0.0773)Region X Month\checkmark\checkmarkRegion X Month\checkmark\checkmarkRegion X Month\checkmark\checkmark\mathcal{O}0.0810.054$	Mall	0.00424	0.0161
Other (0.0133) (0.0119) Other 0.0239 0.0165 Sanitation type (ref: Flush) (0.0147) (0.0136) Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) (0.0197) Other -0.0278 -0.0367^* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) 0.0338^{**} 0.00975 Poorer 0.0338^{**} 0.00975 (0.0138) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0196) (0.0184) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate control 0.221^{***} Precipitation (ref: <100 mm)	vven	-0.00434	-0.0101
Other 0.0239 0.0165 Sanitation type (ref: Flush) (0.0147) (0.0136) Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) Other -0.0278 $-0.0367*$ (0.0223) (0.0198) Wealth quintiles (ref: Poorest) -0.0338^{**} 0.00975 Poorer 0.0338^{**} 0.00975 (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0297^{**} (0.0155) (0.0140) Residence (ref: rural) -0.0176 0.0283 (0.0146) (0.0128) Climate control 0.221^{***} 0.131^{***} Precipitation (ref: <100 mm)		(0.0133)	(0.0119)
$\begin{array}{c ccccc} (0.0147) & (0.0136) \\ \hline Sanitation type (ref: Flush) \\ Pit latrine & 0.0186 & -0.0202 \\ (0.0197) & (0.0176) \\ Other & -0.0278 & -0.0367* \\ (0.0223) & (0.0198) \\ \hline \\ Wealth quintiles (ref: Poorest) \\ Poorer & 0.0338^{**} & 0.00975 \\ (0.0134) & (0.0117) \\ Middle & 0.0919^{***} & 0.0329^{***} \\ (0.0138) & (0.0123) \\ Richer & 0.0891^{***} & 0.0297^{**} \\ (0.0135) & (0.0140) \\ Richest & 0.136^{***} & 0.0603^{***} \\ (0.0196) & (0.0184) \\ Residence (ref: rural) & -0.0176 & 0.00283 \\ (0.0146) & (0.0128) \\ \hline \\ Climate control \\ Precipitation (ref: <100 mm) \\ 100-200 & 0.166^{***} & 0.131^{***} \\ (0.0261) & (0.0248) \\ 200-300 & 0.221^{***} & 0.131^{***} \\ (0.0414) & (0.0382) \\ >300 & 0.143^{*} & 0.0770 \\ (0.0773) & (0.0846) \\ \hline \\ Region X Month & \checkmark & \checkmark \\ Region X Year & \checkmark & \checkmark \\ Observations \\ R-squared & 0.081 & 0.054 \\ \hline \end{array}$	Other	0.0239	0.0165
Sanitation type (ref: Flush) (0.018) (0.019) Pit latrine 0.0186 -0.0202 (0.0197) (0.0176) Other -0.0278 -0.0367^* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) 0.0338^{**} 0.00975 Poorer 0.0338^{**} 0.00975 (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0297^{**} (0.0155) (0.0140) (0.0128) Climate control -0.0176 0.00283 Precipitation (ref: <100 mm)		(0.0147)	(0.0136)
Pit latrine0.0186-0.0202Pit latrine (0.0197) (0.0176) Other -0.0278 $-0.0367*$ (0.0223) (0.0198) Wealth quintiles (ref: Poorest) (0.0223) Poorer $0.0338**$ 0.00975 (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0196) (0.0144) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)	Sanitation type (ref: Flush)		
Pit fatmle 0.0180 -0.0202 Other (0.0197) (0.0197) Other -0.0278 -0.0367^* (0.0223) (0.0198) Wealth quintiles (ref: Poorest) (0.0223) Poorer 0.0338^{**} 0.00975 (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0138) (0.0123) Richest 0.136^{***} 0.0297^{**} (0.0196) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0196) (0.0184) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate control (0.0261) (0.0248) $200-300$ 0.221^{***} 0.131^{***} $200-300$ 0.143^{*} 0.0770 (0.0773) (0.0846) Region X Month \checkmark \checkmark Region X Month \checkmark \checkmark Region X Month \checkmark \checkmark Region X Month 0.081 0.054	Dit latering	0.0106	0.0000
$\begin{array}{ccccccc} (0.0197) & (0.0176) \\ 0 \text{ ther} & -0.0278 & -0.0367^{\ast} \\ (0.0223) & (0.0198) \\ \end{array} \\ \hline \\ \text{Wealth quintiles (ref: Poorest)} \\ \text{Poorer} & 0.0338^{**} & 0.00975 \\ (0.0134) & (0.0117) \\ \text{Middle} & 0.0919^{***} & 0.0329^{***} \\ (0.0138) & (0.0123) \\ \text{Richer} & 0.0891^{***} & 0.0297^{**} \\ (0.0135) & (0.0140) \\ \text{Richest} & 0.136^{***} & 0.0603^{***} \\ (0.0196) & (0.0184) \\ \text{Residence (ref: rural)} & -0.0176 & 0.00283 \\ (0.0146) & (0.0128) \\ \hline \\ \text{Climate control} \\ Precipitation (ref: <100 \text{ mm}) \\ 100-200 & 0.166^{***} & 0.131^{***} \\ (0.0261) & (0.0248) \\ 200-300 & 0.221^{***} & 0.131^{***} \\ (0.0414) & (0.0382) \\ >300 & 0.143^{*} & 0.0770 \\ (0.0773) & (0.0846) \\ \hline \\ \text{Region X Month} & \checkmark & \checkmark \\ \hline \\ \text{Region X Year} & 238,253 \\ \hline \\ \text{Observations} \\ \hline \\ \text{R-squared} & 0.081 & 0.054 \\ \hline \end{array}$	Pit latrine	0.0180	-0.0202
Other -0.0278 -0.0367^* Wealth quintiles (ref: Poorest) (0.0123) (0.0198) Poorer 0.0338^{**} 0.00975 (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0297^{**} (0.0155) (0.0140) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate control Precipitation (ref: <100 mm)		(0.0197)	(0.0176)
$\begin{array}{c cccc} (0.0223) & (0.0198) \\ \hline & & & & & & \\ & & & & & & \\ & & & &$	Other	-0.0278	-0.0367*
Wealth quintiles (ref: Poorest) Poorer 0.0338^{**} $0.00975(0.0134)0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0329^{***}0.0138)(0.0123)Richer0.0329^{***}0.0297^{***}0.0297^{***}0.0138)(0.0123)0.0291^{***}0.01655)(0.0140)Richest0.039^{***}0.0603^{***}0.00283(0.0146)(0.0128)Climate controlPrecipitation (ref: <100 mm)100-2000.166^{***}0.0261)(0.0248)200-3000.221^{***}0.131^{***}(0.0414)(0.0382)>300\sqrt{4}\sqrt{4}\sqrt{5}Region X MonthRegion X Year\sqrt{4}\sqrt{5}\sqrt{4}\sqrt{5}ObservationsR-squared238,2530.081238,2530.054$		(0.0223)	(0.0198)
Poorer 0.0338^{**} 0.00975 Poorer (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} Richer 0.0891^{***} 0.0297^{**} (0.0138) (0.0123) Richest 0.136^{***} 0.0297^{**} (0.0155) (0.0140) (0.0145) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) (0.0146) Climate controlPrecipitation (ref: <100 mm)	Wealth quintiles (ref: Poorest)		
Poolei $0.0333 - 0.00917$ Middle (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} Richest 0.136^{***} 0.0297^{**} (0.0155) (0.0140) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)	Deorer	0 0000**	0.00075
Middle (0.0134) (0.0117) Middle 0.0919^{***} 0.0329^{***} (0.0138) (0.0123) Richer 0.0891^{***} 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0196) (0.0184) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)	FUUIEI	0.0338""	0.009/5
Middle 0.0919^{***} 0.0329^{***} Richer (0.0138) (0.0123) Richer 0.0891^{***} 0.029^{***} (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0196) (0.0184) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)		(0.0134)	(0.0117)
Richer $\begin{pmatrix} (0.0138) & (0.0123) \\ 0.0891^{***} & 0.0297^{**} \\ (0.0155) & (0.0140) \\ 0.136^{***} & 0.0603^{***} \\ (0.0196) & (0.0144) \\ 0.0196) & (0.0184) \\ 0.0146) & (0.0128) \\ \hline Climate controlPrecipitation (ref: <100 mm) 100-200 & 0.166^{***} & 0.109^{***} \\ (0.0261) & (0.0248) \\ 200-300 & 0.221^{***} & 0.131^{***} \\ (0.0414) & (0.0382) \\ >300 & 0.143^{*} & 0.0770 \\ (0.0773) & (0.0846) \\ \hline Region X Month & \checkmark & \checkmark \\ Region X Year & \checkmark & \checkmark \\ Observations & 238,253 & 238,253 \\ R-squared & 0.081 & 0.054 \\ \hline \end{tabular}$	Middle	0.0919***	0.0329***
Richer 0.0891^{***} 0.0297^{**} Richer 0.0297^{**} (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} (0.0140) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)		(0.0138)	(0.0123)
Number (0.0155) (0.0140) Richest 0.136^{***} 0.0603^{***} Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)	Richer	0.0891***	0.0297**
Richest (0.0135) (0.0136) Richest 0.136^{***} 0.0603^{***} (0.0196) (0.0184) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)		(0.0155)	(0.0140)
ruchest 0.136^{+} 0.0603^{***} Residence (ref: rural) (0.0196) (0.0184) Residence (ref: rural) -0.0176 0.00283 (0.0146) (0.0128) Climate controlPrecipitation (ref: <100 mm)	Dishaat	0.12(***	0.0140)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	KICHEST	0.136^^^	0.0603^^^
Residence (ref: rural) -0.0176 (0.0128) 0.00283 (0.0128)Climate control (0.0146) (0.0128) Precipitation (ref: <100 mm)		(0.0196)	(0.0184)
$\begin{array}{c} \text{(0.0146)} & (0.0128) \\ \hline \text{Climate control} \\ & \\ \text{Precipitation (ref: <100 mm)} \\ 100-200 & 0.166^{***} & 0.109^{***} \\ & (0.0261) & (0.0248) \\ 0.021^{***} & 0.131^{***} \\ & (0.0414) & (0.0382) \\ >300 & 0.143^{*} & 0.0770 \\ & (0.0773) & (0.0846) \end{array}$	Residence (ref: rural)	-0.0176	0.00283
Climate control $(0.0110)^{\circ}$ Precipitation (ref: <100 mm)		(0.0146)	(0.0128)
Precipitation (ref: <100 mm)	Climate control	()	(
Precipitation (ref: < 100 mm) $100-200$ 0.166^{***} 0.109^{***} $200-300$ 0.221^{***} 0.131^{***} 0.0414 (0.0382) >300 0.143^{*} 0.0770 0.0773 (0.0846) Region X Month \checkmark \checkmark Region X Year \checkmark \checkmark Observations $238,253$ $238,253$ R-squared 0.081 0.054	Description (usf: 100)		
$100-200$ 0.166^{***} 0.109^{***} (0.0261) (0.0248) $200-300$ 0.221^{***} 0.131^{***} >300 0.143^* 0.0770 (0.0773) (0.0846) Region X Month \checkmark \checkmark \checkmark \checkmark Observations $238,253$ $238,253$ R-squared 0.081 0.054	recipitation (ref: <100 mm)	0.465	0.405
$\begin{array}{cccc} (0.0261) & (0.0248) \\ 0.221^{***} & 0.131^{***} \\ (0.0414) & (0.0382) \\ >300 & 0.143^{*} & 0.0770 \\ (0.0773) & (0.0846) \end{array}$	100-200	0.166***	0.109***
$\begin{array}{cccc} 200-300 & 0.221^{***} & 0.131^{***} \\ (0.0414) & (0.0382) \\ >300 & 0.143^{*} & 0.0770 \\ (0.0773) & (0.0846) \end{array}$		(0.0261)	(0.0248)
>300 (0.0414) (0.0382) >300 0.143^* 0.0770 (0.0773) (0.0846) Region X Month \checkmark \checkmark \checkmark \checkmark \checkmark Observations 238,253 238,253 R-squared 0.081 0.054	200-300	0.221***	0.131***
$\begin{array}{cccc} (0.0414) & (0.0322) \\ & & 0.143^{*} & 0.0770 \\ (0.0773) & (0.0846) \end{array}$ Region X Month \checkmark \checkmark Region X Year \checkmark \checkmark \checkmark \checkmark \checkmark Observations 238,253 R-squared 0.081		(0.0414)	(0 0383)
> 300 0.143° 0.0770 (0.0773) (0.0846) Region X Month ✓ ✓ ✓ ✓ ✓ Observations 238,253 238,253 R-squared 0.081 0.054	> 200	0.140*	0.0302)
(0.0773) (0.0846) Region X Month ✓ ✓ Region X Year ✓ ✓ Observations 238,253 238,253 R-squared 0.081 0.054	>300	0.143*	0.0770
Region X MonthImage: Constraint of the second s		(0.0773)	(0.0846)
Region X Month Region X Year✓✓Øbservations R-squared238,253 0.081238,253 0.054			
Region X Year ✓ ✓ Observations 238,253 238,253 R-squared 0.081 0.054	Region X Month	\checkmark	\checkmark
Observations 238,253 238,253 R-squared 0.081 0.054	Region X Vear		
Observations 238,253 238,253 R-squared 0.081 0.054	ingion A ica	v	v
Observations 238,253 238,253 R-squared 0.081 0.054			
R-squared 0.081 0.054	Observations	238,253	238,253
	R-squared	0.081	0.054

Robust standard errors in parentheses clustered at the EA level

*** p < 0.01, ** p < 0.05, * p < 0.1*Notes*: Unconditional quantile regression with high dimensional fixed-effects by (Rios-Avila, 2020). Fixed effects are with respect to the month and year of the interview.

C.11 UQR - Alternative decision making indicator

Dependent variable: WHZ	Q10	Q25	Q50	Q75	Q90
Variables	(1)	(2)	(3)	(4)	(5)
					. ,
Heat exposure (>30 °C)	-0.124***	-0.131***	-0.157***	-0.154***	-0.198***
	(0.0409)	(0.0262)	(0.0223)	(0.0248)	(0.0353)
Decision making	0.00255	0.0301**	0.00904	0.00787	-0.0118
-	(0.0201)	(0.0140)	(0.0126)	(0.0149)	(0.0220)
Heat exposure X Decision making	0.0983***	0.0216	0.0274*	0.0178	0.0418
-	(0.0315)	(0.0198)	(0.0162)	(0.0182)	(0.0265)
Child characteristics	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Maternal characteristics	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Household characteristics	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Climate control	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Region X Month	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Region X Year	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations	247,724	247,724	247,724	247,724	247,724
R-squared	0.069	0.080	0.071	0.054	0.040

Table C.11.1: UQR results using the alternative decision making indicator

Robust standard errors in parentheses clustered at the EA level

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

Notes: Unconditional quantile regression with high dimensional fixed-effects by (Rios-Avila, 2020). Fixed effects are with respect to the month and year of the interview.

C.12 UQR - Decision making tertiles

Dependent variable: WHZ Variables	Q10 (1)	Q25 (2)	Q50 (3)	Q75 (4)	Q90 (5)
Heat exposure (>30 °C)	-0.131***	-0.134***	-0.157***	-0.142***	-0.194***
	(0.0423)	(0.0269)	(0.0229)	(0.0253)	(0.0362)
Decision making tertiles (ref: 1 st tertile)					
2 nd tertile	0.0244	0.0295*	0.00943	0.0122	-0.0288
	(0.0219)	(0.0153)	(0.0139)	(0.0162)	(0.0242)
3 rd tertile	-0.0173	0.0324**	0.00262	0.0209	0.00236
	(0.0230)	(0.0159)	(0.0145)	(0.0167)	(0.0247)
Heat X Dec (ref: 1 st tertile)					
Heat X Dec 2 nd tertile	0.0960***	0.0192	0.0297*	0.0172	0.0674**
	(0.0350)	(0.0219)	(0.0180)	(0.0201)	(0.0293)
Heat X Dec 3 rd tertile	0.0918**	0.0178	0.0161	-0.0216	-0.0102
	(0.0375)	(0.0236)	(0.0195)	(0.0216)	(0.0315)
Child characteristics	\checkmark	\checkmark	\checkmark	\checkmark	1
Maternal characteristics			· √		
Household characteristics	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Climate control	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Region X Month	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Region X Year	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations	238,253	238,253	238,253	238,253	238.253
R-squared	0.069	0.081	0.071	0.054	0.041

Table C.12.1: UQR	results using	decision	making	tertiles
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Robust standard errors in parentheses clustered at the EA level *** p < 0.01, ** p < 0.05, * p < 0.1*Notes*: Unconditional quantile regression with high dimensional fixed-effects by (Rios-Avila, 2020). Fixed effects are with respect to the month and year of the interview.

C.13 Nutritional outcomes by wealth quintiles

Variables	Ν	mean	sd	min	max		
	Poorest						
WHZ	103568	-0.384	1.398	-5	4.99		
Wasting (1=yes)	103568	0.114	0.317	0	1		
	Poo	orer					
WHZ	91716	-0.277	1.384	-5	5		
Wasting (1=yes)	91716	0.098	0.298	0	1		
Middle							
WHZ	86500	-0.224	1.377	-5	5		
Wasting (1=yes)	86500	0.091	0.288	0	1		
Richer							
WHZ	78518	-0.201	1.365	-4.99	4.99		
Wasting (1=yes)	78518	0.086	0.28	0	1		
Richest							
WHZ	69249	-0.115	1.343	-5	4.99		
Wasting (1=yes)	69249	0.073	0.26	0	1		

Table C.13.1: WHZ and wasting measures by wealth quintiles