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The Impact of Index Based Livestock Insurance (IBLI) on Child Nutrition in Marsabit County, Kenya

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Abstract

The study uses six rounds of Index-Based Livestock Insurance (IBLI) panel surveys (2009 – 2015) for Northern Kenya's Marsabit county to investigates the impact of IBLI on child nutrition and household food security. We employ Ordinary Least Squares (OLS) and Instrumental Variable (IV) regressions to account for potential endogeneity in IBLI uptake. The results indicate that while IBLI uptake significantly improves the intake of key nutrients such as Vitamin A, protein, iron, and fruits and vegetables, it does not translate into significant improvements in child nutrition status, as measured by Mid-Upper Arm Circumference (MUAC) z-scores. Significant negative effects of age and supplementary feeding on child nutrition, highlight the ongoing nutritional challenges faced by older children and those receiving supplementary food. These results suggest that while IBLI can enhance household food security, it alone is insufficient to address child malnutrition. Comprehensive approaches that integrate financial instruments like IBLI with targeted nutritional interventions and support systems are essential for achieving sustainable improvements in child health outcomes.

Key words: Drought, Child nutrition, food security, livestock, insurance

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List of Abbreviations

ASALs	Arid and Semi-Arid Lands
DHS	Demographic Health Surveys
FCS - N	Food Consumption Scores Nutritional Analysis
HAZ	Height-for-Age z-score
HFIAS	Household Food Insecurity Access Scale
IBLI	Index Based Livestock Insurance
ILRI	International Livestock Research Institute
IV	Instrumental Variable
LSMS	Living Standards Measurement Study
MUAC	Mid-Upper Arm Circumference
NDVI	Normalized Difference Vegetation Index
OLS	Ordinary Least Squares
RCT	Randomized Controlled Trial
TLU	Total Livestock Unit
UNICEF	United Nations International Children's Emergency Fund
WFP	World Food Programme
WHO	World Health Organization

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1.0 Introduction

In regions where agriculture constitutes the backbone of livelihoods, weather-related shocks, particularly droughts, pose severe economic, health, and welfare challenges (Barrett et al., 2004; Marra et al., 2003). These shocks lead to food insecurity as households are forced to reduce food intake and face uncertainty in accessing nutritionally adequate and safe food (Drameh et al., 2019). The situation is exacerbated in developing regions with low socioeconomic status (SES), resulting in the consumption of inadequate quantities and low-quality foods (Maskooni et al., 2013).

Food insecurity at the household level jeopardizes dietary intake, leading to broad consequences, including psychosocial dysfunction among household members, especially children, socioeconomic predicaments, and poor overall health status (Aguyawo et al., 2010; Nnakwe et al., 2013). Children are particularly affected due to their high nutrient demands for growth (Rah et al., 2010), which can result in low school admission, absenteeism, early dropout, and low academic achievement, ultimately reducing productivity in adulthood (Aguyawo et al., 2010).

Malnutrition, a major outcome of food insecurity, has dramatically increased over the past decade from 5.5 million cases to over 30 million, resulting in the deaths of more than 3.5 million children under the age of five due to inadequate food consumption (Black et al., 2008). By 2022, the number of global deaths among children under five reached 4.9 million, with two-thirds occurring in low- to middle-income regions, primarily in sub-Saharan Africa and Asia (WB, 2022). Research in these regions consistently shows a direct link between household food insecurity and malnutrition in children, manifesting as stunting, being underweight, and wasting (Sorsdahl et al., 2011).

Conventional agricultural insurance and other financial instruments can help rural poor recover from adverse weather shocks and maintain food consumption. However, the insurance market is underdeveloped and not available in many low-income countries, forcing households to undertake coping strategies that include meal rationing, withdrawing children from school, and distress selling of productive assets (Barrett et al., 2004; Marra et al., 2003; Dercon and Christiaensen, 2011; Simtowe, 2006). These short-term survival strategies, while necessary, potentially entrench households deeper into poverty and food insecurity, undermining their long-term resilience and capacity to thrive, perpetuating a cycle of poverty across generations (Carter et al., 2007; Barrett, 2011; Zimmerman et al., 2003).

In recent years, index-based insurance, which uses weather or environmental parameters such as rainfall, temperature, or remotely sensed estimates of vegetation levels as proxies for losses, has been introduced as an alternative to traditional micro-insurance (Chantarat et al., 2013). Payouts from index insurance have been shown to smooth household food consumption, income fluctuations, shield productive assets, encourage the adoption of credit and improved agricultural technologies, and ultimately enhance various dimensions of household welfare (Barnett et al., 2008; Jensen et al., 2018; Smith, 2016). Characterized by its efficiency in reducing transaction costs associated with monitoring and verification, index-based insurance has significantly improved weather risk management in two principal ways (Toth et al., 2017; Tafere et al., 2018). Firstly, by providing timely payouts in response to extreme weather events, which assist insured households in maintaining consistent consumption levels and preserving productive assets that might otherwise be liquidated under distress. Secondly, by offering financial certainty regarding future income.

Accumulating empirical evidence emphasizes the impact of index insurance on economic resilience and household welfare, yet comprehensive analyses remain (Cole et al., 2017; Hill et al., 2017; Jensen et al., 2017; Toth et al., 2017; Bertram-Huemmer & Kraehnert, 2018; Janzen & Carter, 2018; Tafere et al., 2018; Matsuda & Kurosaki, 2019). Particularly, the consequences of index insurance on the nutritional status of children within households. This study builds on previous research demonstrating that Index-Based Livestock Insurance (IBLI) significantly enhances households' well-being, primarily by reducing risk exposure (Jensen, Barrett, & Mude, 2015; Jensen, Ikegami, & Mude, 2015). Additionally, IBLI has been shown to positively impact subjective well-being (Tafere et al., 2015; Hirfrfot et al., 2014), with purchases of IBLI linked to significant improvements in self-reported well-being. Notably, even when insurance policies do not result in payouts, they can still provide substantial benefits to poor rural populations by enhancing their overall resilience and economic stability.

The purpose of this study is to assess the effect of IBLI on children under five years of age through its association with food insecurity in rural households. The study is directed towards program managers implementing financial instrument initiatives for resilience, practitioners in the field of nutrition, authorities, and policymakers regarding the situation and challenges of financial instruments for resilience and child development in developing regions.

The remainder of the paper is structured as follows: sections 2 provide a review of literature, section 3, Data and methodology, section 4 presents the results and discussion and 5, the conclusion.

2.0 Literature review

This chapter provides a review of the existing literature on drought, food insecurity, and IBLI and their impacts on child nutrition and household food security. The review is structured into three main sections: the association between drought and malnutrition among children, the relationship between food insecurity and nutrition quality, and the role of IBLI as a tool for risk management. By examining these areas, we aim to contextualize the challenges faced by pastoral communities in Marsabit County and the potential benefits of IBLI in mitigating these challenges.

2.1 Drought and its association with malnutrition among children

Households facing drought conditions adopt coping strategies such as meal rationing, withdrawing children from school, and distress selling of productive assets. These actions disrupt their economic stability and welfare, pushing households deeper into poverty and food insecurity, thereby undermining their long-term resilience and perpetuating a cycle of poverty across generations (Barrett et al., 2004; Marra et al., 2003; Dercon et al., 2011; Simtowe, 2006). Patel et al. (2019) highlights the catastrophic impacts of extreme weather events, emphasizing the role of climate change in exacerbating these effects, especially in developing countries where resources are scarce, adaptive capacities are limited, and dependence on climate-sensitive livelihoods is high.

The IPCC (2014) and Bachmair et al. (2016) discuss both the direct and indirect ways droughts affect adults and children, such as through reduced water and food availability, high food prices, and the mental health impacts stemming from uncertainty and financial stress. Ochieng et al. (2017), in their analysis of Baringo area rainfall data in Kenya, report significant fluctuations, with periods of heavy rainfall followed by severe droughts, affecting household food availability and access, and increasing malnutrition in children during low rainfall periods. Additionally, Watts et al. (2017) and Lohmann & Lechtenfeld (2015) found that children in agricultural communities face heightened risks during droughts, with food insecurity directly leading to malnutrition and undernutrition, critically affecting their growth and immune systems.

Venkaiah et al. (2015) find significant nutritional challenges in drought-affected areas, where dietary intakes are substantially below the recommended daily allowances, particularly for micronutrients essential for child growth and development. This is exacerbated by the lack of access to diversified foods, leading to micronutrient malnutrition and increased vulnerability to undernutrition among children under five years of age. The 2015 UNICEF Annual Report emphasizes the broader humanitarian context in drought-prone areas, affecting not only nutrition but also increasing the risk of diseases and exacerbating vulnerabilities among children.
Stanke et al. (2013) add that drought conditions exacerbate the prevalence of both water-borne (such as cholera, hepatitis, and diarrhea) and vector-borne diseases (including malaria and dengue), further endangering children's health. The scarcity of clean water and reduced hygiene during droughts increase the likelihood of these diseases, major contributors to child mortality and morbidity.

Pandey et al. (2007) report a specific consequence of drought—its significant impact on education due to economic strains on families. The inability to afford schooling costs or the necessity for children to contribute to the family income leads to school withdrawals, affecting long-term educational and developmental prospects.

2.2 Food insecurity and nutrition quality

Food insecurity remains a predominant risk factor for child malnutrition, impacting both the consumption and the nutritional quality of food. Black et al. (2013) identify food insecurity as a critical factor that leads to reduced intake of essential macronutrients such as energy, protein, and micronutrients (Ijaromotimi et al., 2013). This inadequacy in dietary intake compromises a child's nutritional status, ultimately affecting their health (Demissie et al., 2013).

Campbell (1991) noted that food insecurity contributes to suboptimal nutritional outcomes and constrains the quality of healthy living among children. Malnutrition arises from a range of factors spanning immediate (individual level), underlying (household or family level), and basic (societal level) causes. These interrelated factors influence each other, where diseases and inadequate food intake affect the immediate causes at the individual level (Quisumbing et al., 2009). The focus is often on underlying factors like household food insecurity, unhealthy living environments, poor health services, and inadequate care and feeding practices (UNICEF, 1990). Basic causes reflect broader societal issues-cultural, structural, economic, and political processes that impact the availability of financial, human, physical, and social capital, subsequently affecting household access to adequate resources (Sanfilippo et al., 2012).

Severe food insecurity in a household suggests a high nutritional risk (Campbell, 1991). The conceptual framework by the United Nations International Children's Emergency Fund (UNICEF) outlines that food security and health are the primary determinants of a child's nutritional status, as detailed in their malnutrition framework (Frongillo et al., 1997). Research in Sub-Saharan Africa shows that poor-quality diets associated with household food insecurity led to negative health outcomes, including obesity, chronic diseases, and nutritional disorders in children (Akombi et al., 2017; Demissie et al., 2013).

Nonetheless, addressing food insecurity at the household level is fraught with challenges. Firstly, the ability of a household to acquire adequate food does not necessarily equate to making nutritious food purchases. Families might prioritize other essentials, such as school fees and housing, over nutritious food (Clark et al., 2009). Secondly, food allocation strategies within households may not always consider the nutritional needs of each member. Dr. Naoko Yamamoto, Assistant Director-General at the World Health Organization (WHO), emphasizes the need for quality health services and universal health coverage to include nutrition as a cornerstone of essential health packages. Improving food environments is crucial for enabling healthier diets for all (WHO, 2019).

2.3 Index-Based Livestock Insurance (IBLI) as a Tool for Risk Management

IBLI has transformed risk management strategies for pastoralists in the arid and semi-arid lands (ASALs) of the Horn of Africa. Historically vulnerable to frequent droughts, these communities found traditional insurance mechanisms and humanitarian aid inadequate in covering the economic shocks experienced. IBLI uses satellite imagery to monitor the Normalized Difference Vegetation Index (NDVI), offering a more sustainable alternative by enabling payouts based on environmental conditions that directly affect livestock health and productivity (Bageant & Barrett, 2015; Janzen & Carter, 2013).

Further investigations into IBLI's impact reveal that microinsurance, including IBLI, serves as a crucial safety net. It helps smooth consumption and nutrition while preventing the depletion of critical assets among impoverished households in low-income countries. These microinsurance mechanisms enable better management of both anticipatory and reactionary risks, promoting investments in higher-risk, higher-return activities (Barrett et al., 2007; Skees & Collier, 2008; Dercon et al., 2008).

Using randomized controlled trial (RCT) data from rural Kenya, Janzen & Carter (2013) estimate that IBLI reduces dependence on costly coping strategies. It is particularly effective in helping wealthier households avoid asset liquidation and aiding poorer households in minimizing consumption cuts following a shock. This differentiated coping strategy, influenced by household wealth, highlights the complex interplay between insurance coverage and economic behavior in adversity. Wealthier households typically cope by selling assets, a likelihood significantly reduced by insurance. Conversely, less affluent households, often responding to shocks by cutting food consumption, benefit from insurance through a reduced reliance on this strategy, demonstrating a nuanced understanding of IBLI's impact.

Moreover, the role of weather index insurance in facilitating access to agricultural inputs and finance is crucial. By bundling insurance with high-yield crop varieties or linking it with credit services, insurance can significantly enable farmers to invest in improved agricultural practices and inputs, thus enhancing productivity and food security amid climatic uncertainties (Skees & Barnett, 2006; Barnett, Barrett, & Skees, 2008).

Noritomo et al. (2019) explore the welfare-enhancing effects of index-based insurance through two pathways: mitigating weather-related shocks via payouts and inducing policyholders to take greater yet more profitable risks. The study finds that both the risk-management and payout effects of index insurance contribute to reducing the likelihood of distress sales of livestock. Furthermore, the payout effects lead to a reduced slaughter of livestock, suggesting that insurance payouts assist people in escaping from poverty traps more effectively than do behavioral changes induced by insurance purchases.

Matsuda et al. (2019) investigate the direct and indirect impacts of index-based livestock insurance in southern Ethiopia, emphasizing the importance of such financial products in enhancing the resilience of pastoral communities to climatic variabilities and shocks. The overarching theme of leveraging insurance as a coping and adaptation strategy aligns with the insights provided by Noritomo et al. (2019).

The growing acceptance of IBLI among pastoral communities, driven by factors such as price incentives and educational efforts, highlight its perceived value in mitigating specific risks faced by pastoralists in ASALs. Comparative evaluations with programs like the Hunger Safety Net Program highlight IBLI's cost-effectiveness as a social protection tool, further validating its significance in the broader context of risk management strategies tailored for vulnerable populations (Bageant & Barrett, 2015).

These studies emphasize the need for integrated approaches that not only provide immediate relief through financial instruments like insurance but also address broader socio-economic factors, such as education and access to health information, which significantly influence children's long-term well-being.

3.0 Data and Methodology

This chapter outlines the data and methodological approaches used to investigate the impact of IBLI on child nutrition and household food security. We provide a detailed description of the IBLI product, the study setting, research design, variables, and measurements, as well as the econometric methodology employed to address potential endogeneity issues.

3.1. Index-Based Livestock Insurance Product in Marsabit County, Kenya

To aid pastoral households in managing the severe impacts of drought and drought-related livestock mortality, the IBLI project was launched in Marsabit district in January 2010 by the International Livestock Research Institute (ILRI) and Cornell University. IBLI employs a forage scarcity index, measured by the Normalized Difference Vegetation Index (NDVI) captured via satellite (Chantarat et al., 2013; Takahashi et al., 2016). Since its inception, the insurance has been offered for purchase biannually, in the months of August–September and January–February, strategically before the onset of the rainy seasons. The premiums vary across different areas of the district, reflecting the drought-related risks specific to each geographic location.

Payouts are activated when the forecasted livestock mortality index surpasses 15%, with the payout amount escalating in correlation with the mortality index. There are two designated payout periods, in October and March, following each dry season. Households that maintain overlapping policies by purchasing coverage in two consecutive sales periods are eligible to receive payouts for both. To secure an IBLI policy for one year, households decide on the number of Total Livestock Units (TLUs) they wish to insure for that period (Noritomo et al., 2019). This structure aims to provide a substantial safety net for pastoralists, mitigating the financial strain caused by drought-induced livestock losses.

3.2. Study Setting

The data for this study were collected from Marsabit District in Northern Kenya, a predominantly arid and semi-arid region where the majority of the population engages in pastoral livelihoods, primarily raising cattle, camels, goats, and sheep. The study encompassed 16 sub-locations: Dakabaricha, Dirib Gombo, Sagante, Bubisa, El Gade, Kalacha, Turbi, Karare, Kargi, Kurkum, Logologo, Illaut, Lontolio, Loyangakani, Ngurunit, and South Horr. The region is characterized by a bi-modal rainfall pattern with four distinct seasons: a long rainy season from March to May, a short rainy season from October to December, a long dry season from June to September, and a short dry season from January to February. The data were collected annually, primarily in November, focusing on the same households across all seven periods starting from 2009.

Livestock serves as the primary income source for households in this area, which often maintain semi-permanent settlements alongside mobile herds that roam in search of pasture and water during periods of seasonal forage scarcity. The region is prone to catastrophic herd losses, particularly during consecutive seasons of unexpectedly low rainfall (Chantarat et al., 2017). Marsabit has endured nearly 30 droughts over the past century, including four in the last fifteen years alone (Noritoma et al., 2019). These conditions, combined with high drought-related livestock mortality rates—reaching 50%–80% for cattle and 30% for sheep and goats—often plunge many pastoralists into poverty traps, leading to prolonged periods of economic hardship (Lybbert et al., 2004; Santos and Barrett, 2011; Takahashi et al., 2019).

3.3. Research Design

In 2009, a baseline household survey was conducted in Marsabit District, capturing critical data across a variety of parameters including herd dynamics, incomes, child health, household food security, risk experiences and behaviors, demographics, and educational outcomes. The survey incorporated two innovative elements aimed at enhancing the research design. The first involved randomized encouragement treatments to explore and test the demand for key program parameters. As part of this treatment, a sub-sample of households was selected to participate in an educational game that simulated the pastoral production system. This game was designed to illustrate how IBLI responds to both idiosyncratic and covariate shocks. It was conducted in nine of the 16 sites, involving a random selection of half the households in each sampled site, just before the launch of IBLI sales in January 2010 (McPeak et al., 2010).

The second encouragement treatment used was the distribution of discount coupons. These coupons were randomly handed out to approximately 60% of the surveyed households before each sales season. The discounts varied, with coupons offering reductions of 10%, 20%, 30%, 40%, 50%, and 60%. These coupons could be presented to insurance sales agents, entitling the household to the corresponding discount on premiums for the first 15 Total Livestock Units (TLUs) insured during that sales period. The coupons were only valid until the end of the sales period immediately following their distribution, and a new round of random coupon distribution was implemented for each subsequent sales season (Chantara et al, 2014).

Data collection was carried out over seven annual survey rounds (Appendix 2), spanning from the beginning of 2009 to the end of 2020. This longitudinal approach allows for an in-depth analysis of the impact and evolution of the IBLI program over a significant period.

3.4. Variables and Measurements

3.4.1. Food Security/Insecurity

Food security is a multifaceted and multidimensional concept that encompasses availability, access, utilization, and stability, making it impossible for a single measure to capture all its dimensions comprehensively (Coates et al., 2012; Coates, 2013; Jones et al., 2013; Tadesse et al., 2020). Consequently, analysts employ a diverse set of proxy indicators to capture different aspects of food security/insecurity, categorized into objective and subjective/experiential measures.

Objective measures include calorie intake or availability, monetary poverty thresholds, and dietary diversity (Headey et al., 2012; Tadesse et al., 2020). These measures are generally derived from consumption or income data. However, consumption data often exhibit significant seasonal variability and are typically collected via single-round surveys conducted during a specific month each year.

Household surveys on food (in)security, such as those utilizing the Food Consumption Score (FCS) by the World Food Programme, focus on food consumed over the previous four weeks or seven days before the survey. The FCS provides insights into nutrient-rich food groups consumed by the household, crucial for nutritional health and well-being, including proteins, iron, and vitamin A (WFP, 2015). However, consumption data can be prone to errors due to infrequent purchasing patterns or measurement inaccuracies caused by respondents' imperfect recall or reporting biases. Consequently, these data might underreport or overreport the actual food (in)security situation, depending on the survey timing (Gebre et al., 2021).

Thus, objective indicators are limited in their ability to evaluate the seasonality of food insecurity or the impact of shocks unless high-frequency data collection is employed, which can be costly (Tadesse et al., 2020). Large datasets like the Living Standards Measurement Study (LSMS) and Demographic Health Surveys (DHS) enable the analysis of changes over time, providing insights into seasonal variations.

Subjective or experiential measures of food insecurity rely on respondents' perceptions or experiences regarding the availability and access to adequate food. These measures are constructed from responses to direct questions about experiences of food shortages and their consequences. They capture the severity and breadth of food insecurity, from psychological impacts to physical sensations of hunger (Headey and Ecker, 2012). Notable among these is the Food Insecurity Experience Scale (FIES) developed by the United Nations Food and Agriculture Organization's Voice of the Hungry project, which inquires whether respondents have faced difficulties affording food over the past month or year, depending on the focus of the research or program.

Another advanced experiential measure is the Household Food Insecurity Access Scale (HFIAS), developed by the USAID Food and Nutrition Technical Assistance (FANTA) project. The HFIAS is based on the premise that food insecurity causes predictable reactions that can be quantified through surveys and summarized on a scale. It involves nine questions that gauge the occurrence and frequency of food insecurity experiences over a four-week recall period (Coates et al., 2007; Headey and Ecker, 2012).

This paper utilizes the FCS indicator to assess household food insecurity prevalence in Marsabit County, specifically employing the Food Consumption Score Nutritional Analysis (FCS-N) to evaluate food insecurity levels. While this does not provide individual nutrient intake data, the 'Food consumption score nutrition quality analysis' bridges the gap at the household level, linking food access/consumption to nutritional outcomes for children.

To determine nutrient inadequacies, the indicator categorizes nutrient-rich food groups based on consumption frequencies, summing up the consumption frequency of food sub-groups within each nutrient-rich group as follows: Vitamin A-rich foods: Dairy, Organ meat, Eggs, Orange vegetables, green vegetables, and orange fruits; Protein-rich foods: Pulses, Dairy, Flesh meat, Organ meat, Fish, and Eggs; Hem iron-rich foods: Flesh meat, Organ meat, and Fish; Oils and fats: Oils and Fats; Staples: Cereals and Tubers; Fruits and vegetables: All fruits and vegetables (including Vitamin A-rich). The frequency of consumption is categorized into: "Never" (0 days) indicating poor food consumption; "Sometimes" (1-6 days) indicating borderline food consumption; "At least daily" (7 days) indicating acceptable food consumption. These categories help analyze the adequacy of food consumption in the studied households (WFP, 2015).

3.4.2. Child Malnutrition

Child malnutrition is a pressing global public health issue (Black et al., 2013). In Kenya, statistics reveal that 26% of children under five years old are stunted, while 11% are underweight. The prevalence of stunting in children under five is higher in rural areas (29%) compared to urban areas (20%) (Takeuchi et al., 2022). Earlier research from 2008 to 2010 in an impoverished urban setting in Nairobi, Kenya, found that nearly half of the children under five were stunted (46–47%), 11–12% were underweight, 2.5–2.6% were wasting, and 9% were overweight or obese. Additionally, 32% of their mothers were overweight or obese, and 7.5% were underweight (Olack et al., 2011). Early detection and intervention are essential given malnutrition's profound and lasting impacts on academic performance, economic productivity (Victora et al., 2008), and health-related quality of life (Williams et al., 2005).

Mid-upper arm circumference (MUAC) measurement provides a simple and reliable method for screening nutritional status and is useful for rapid assessment in large population studies. Traditionally, MUAC has been a practical proxy for undernutrition, particularly severe acute malnutrition in infants, children under five years (Goossens et al., 2012), and pregnant women (Tang et al., 2013). Studies show that the probability of acute malnutrition as defined by MUAC varies with height-for-age z-score (HAZ) in Cambodian infants under 30 months (Wieringa et al., 2018). Additionally, MUAC has been proven as a reliable predictor of mortality risk in various populations, including Gambian infants (Mwangome et al., 2012), Southeast African children and adolescents (Mramba et al., 2017), and older adults in Taiwan (Weng et al., 2018).

Recent studies have highlighted MUAC's accuracy in detecting underweight and overweight among schoolchildren in South Africa (Craig et al., 2014) and the Netherlands (Talma et al., 2019), although the cutoffs for overweight in these studies have shown inconsistencies. In this study, we use MUAC for age Z-scores to assess undernutrition and overnutrition in children under five years of age in Marsabit County. This approach allows us to effectively analyze the nutritional status of 3,713 children under 5 years of age in 632 households effectively based on reliable measurements.

3.4.3. Index-Based Livestock Insurance

In this study, we use IBLI uptake and discount coupons to establish causality. Discount coupons, distributed randomly to approximately 60% of surveyed households before each sales season, offer varying levels of premium reductions (10%, 20%, 30%, 40%, 50%, and 60%) for insuring up to 15 TLUs (1 TLU = 0.7 camels, 1 cow, 10 goats or sheep). Households were classified into three wealth classes based on livestock holdings: (1) low, meaning less than 10 TLU; (2) medium, with between 10 and 20 TLU; and (3) high, owning more than 20 TLU. In nearly all cases a TLU class could be identified for the households in the population. This design allows us to analyze the impact of IBLI on household food security and child malnutrition by examining the relationship between insurance uptake and nutritional outcomes.

3.5 Econometric methodology

Evaluating policy interventions where participants can choose to "opt-in" presents significant challenges due to the potential non-random nature of program selection. Participation may be systematically linked to both observable and unobservable characteristics of respondents. In the case of IBLI, uptake is likely endogenous, meaning individuals' subjective life satisfaction is probably correlated with their risk perceptions, planning horizons, and other unobserved factors influencing their decision to adopt insurance. The IBLI impact evaluation's experimental design, which includes randomized exposure to various extension treatments and the randomized distribution of premium discount coupons, helps address the selection bias associated with insurance uptake decisions. By first estimating the factors influencing IBLI uptake and then examining the impact of estimated IBLI uptake on children's health and household food consumption, we can derive causal estimates of IBLI's effects.

3.5.1 Model Specification

As discussed, discount coupons for insurance premiums were distributed randomly among all the insurance sales periods. These coupons provide exogenous variations and are used as instruments for IBLI uptake in estimating the effect of IBLI Insurance on Child Nutrition.

The First Stage regression for household *i* at time (round) *j* can be expressed as,

$\mathrm{Ins}_{\mathrm{ij}} = \pi_0 + \pi_1 \cdot \mathrm{ibli\_disc}_{\mathrm{ij}} + \pi_2 \cdot \mathrm{age}_{ij} + \pi_3 \cdot \mathrm{sf}_{ij} + \pi_4 \cdot \mathrm{TLU}_{i}\mathrm{j} + u_{ij}$ …………………………… *(1)*

Where $\mathrm{Ins}_{\mathrm{ij}}$ is a dummy variable indicating whether household *i* in round *j* purchased IBLI, $\mathrm{ibli\_disc}_{\mathrm{ij}}$ is the exogenously given discount rate, $\mathrm{age}_{ij} + \pi_3 \cdot \mathrm{sf}_{ij} + \pi_4 \cdot \mathrm{TLU}_{ij}$ are covariates that affect child nutrition for both policy holders and non-holders and u_{ij} is the mean zero random error term.

The second-stage regression uses five rounds of post-IBLI panel data, excluding baseline data (round 1), because the insurance product was not available at that time and was yet to be announced publicly. For household *i* and round *j* we run the following regression:

$\mathrm{mfaz}_{\mathrm{i}i} = \beta_0 + \beta_1 \cdot \mathrm{Ins}\hat{} + \beta_2 \cdot \mathrm{age}_{ij} + \beta_3 \cdot \mathrm{sf}_{ij} + \beta_4 \cdot \mathrm{TLU}_{ij} + \rho_I + \rho_{\mathrm{j}} + u_{ij}$ ………………………… *(2)*

Where $\mathrm{mfaz}_{\mathrm{i}i}$ (MUAC for age z score) is the outcome, age_{ij} is the child's age, sf_{ij} is a dummy status of the child receiving supplementary food, TLU_{ij} is the owned livestock in terms of TLU classes, ρ_I and ρ_{j} are the household and time (round) fixed effects, u_{ij} is the random error term and Ins^ is the estimated coefficient of ibli uptake from the first stage. $\beta 1$ represents the effect of IBLI uptake on child nutrition status. $\beta 2$, $\beta 3$, and $\beta 4$ control for the child's age, supplementary food status, and livestock holdings, respectively.

Since IBLI was sold twice a year (January–February and August–September) and each policy was effective for one year, there was a timing overlap with the household surveys, which were conducted in October–November to cover household activities over the past year. Therefore, the period during which the insurance was active (without lapsing) varied across different survey rounds. For example, the first follow-up survey conducted in October–November 2010 gathered information from January to September 2010. During this period, the IBLI policy sold in January 2010 was in effect, covering from January 2010 to December 2010.

To estimate the effect of IBLI Insurance on Household Food Consumption Status, the First Stage regression for household *i* can be expressed by,

$\mathrm{Ins}_{\mathrm{ij}} = \pi_0 + \pi_1 \cdot \mathrm{ibli\_disc} + u_i$ …………………… *(3)*

Where Ins_{ij} is a dummy variable indicating whether household *i* in round *j* purchased IBLI, $ibli\_disc_{ij}$ is the exogenously given discount rate u_{ij} is the mean zero random error term.

The second-stage regression uses five rounds of post-IBLI panel data, excluding baseline data (round 1), because the insurance product was not available at that time and was yet to be announced publicly. For household *i* and round *j* we run the following regression:

$fcs_{ij} = \beta_0 + \beta_1 \cdot Ins\hat{}_{ij} + \rho_I + \rho_j u_{ij}$ ………………………………… *(4)*

Where fcs_{ij} (Food Consumption Score for the six nutrition groups i.e. Vitamin A, Protein, Hem iron, Oils and fats, Staples and Fruits and vegetables) is the outcome, ρ_I and ρ_j are the household and time (round) fixed effects, $\beta 1$ represents the effect of IBLI uptake on child nutrition status, u_{ij} is the random error term and Ins^ is the estimated coefficient of ibli uptake from the first stage.

4.0 Results

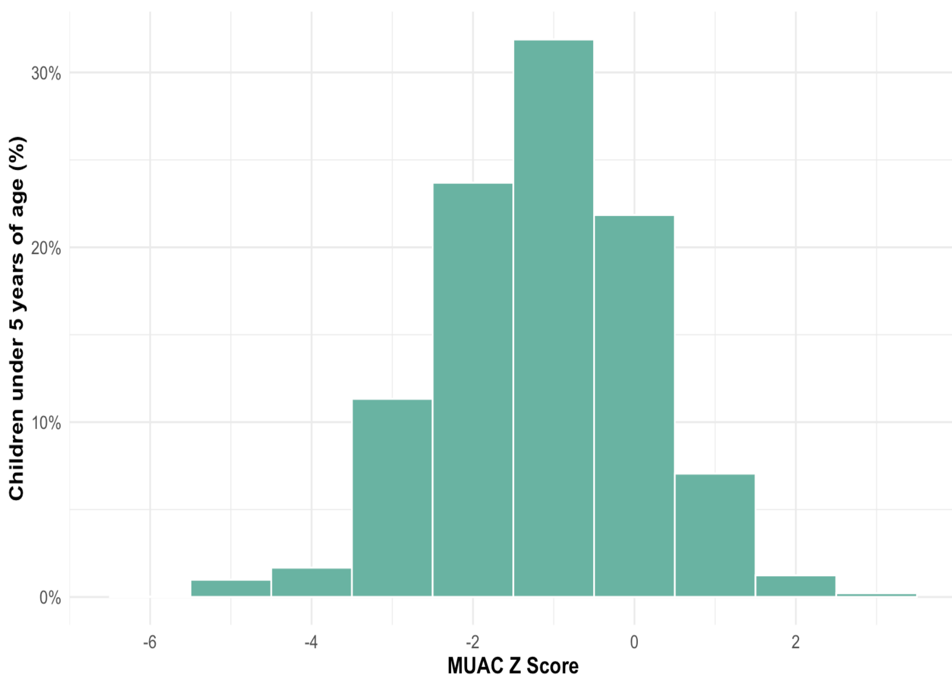
This chapter presents the descriptive analysis and the estimation results providing an overview of the state of child nutrition, dietary diversity, and the adoption of IBLI and the effect of IBLI insurance.

4.1 Descriptive statistics

4.1.1 Child Nutrition Status Over Time

The Z-scores range from a minimum of -5.57 to a maximum of 3.24, with a mean of -1.13 (figure 1). Notably, there is a declining trend in Z-scores over time, with no child maintaining a Z-score above 2 after two years (appendix 1). Children with Z-scores between 0 and 2 are considered to have an acceptable nutritional status, while those with Z-scores below -2 are classified as experiencing extreme malnutrition. This trend underlines the persistent issue of child malnutrition in the study area. Furthermore, the declining trend in MUAC Z-scores as children age, indicate worsening nutritional status over time. This trend is consistent across all 6 rounds of the survey.

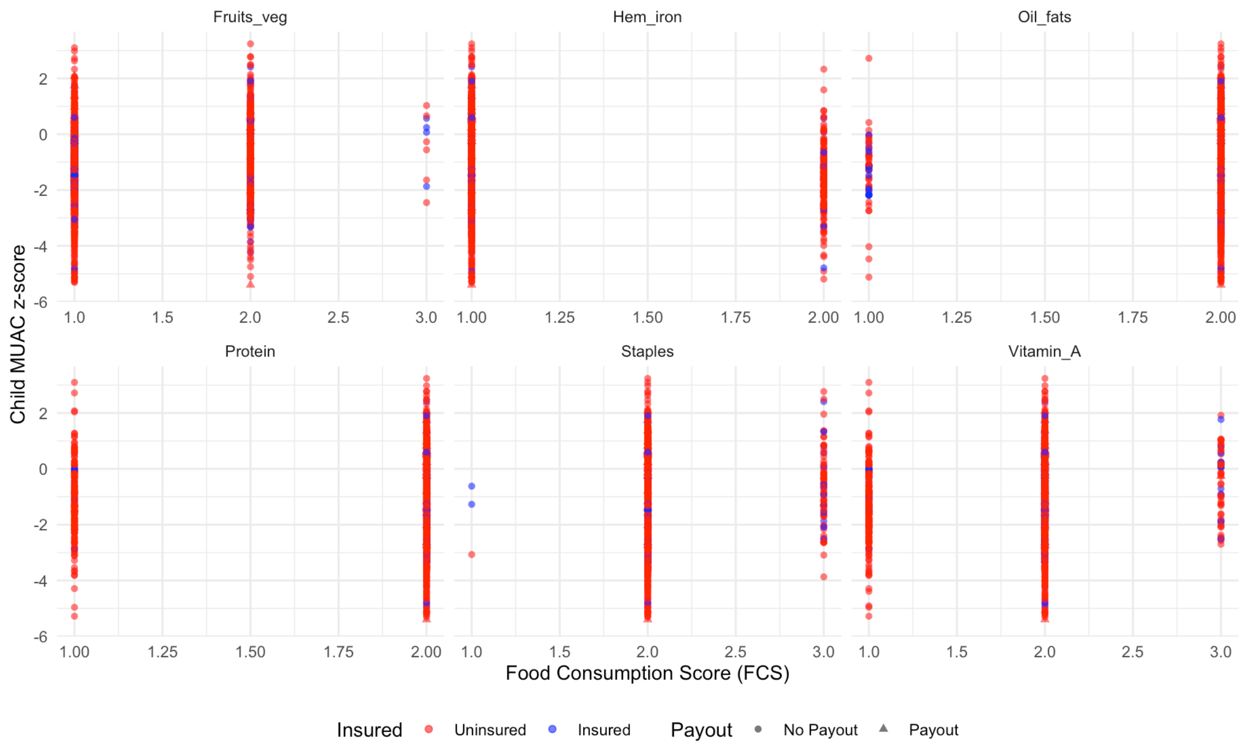
Figure 1: MUAC Z scores distribution



4.1.2 Food Consumption Patterns

The FCS categorizes food intake as follows: 1 = Inadequate, 2 = Borderline, and 3 = Adequate. All households in the area consume staple foods while some households manage to consume Vitamin A, staples, and fruits and vegetables every adequately, as per WFP (2015). This highlights the variability in dietary quality and access to nutrient-rich foods among households. Figure 3 further shows distinct differences between insured and uninsured households. Insured households generally have higher FCS, indicating better dietary diversity and more frequent consumption of nutrient-rich foods. Households that received indemnity payouts tend to have higher scores, particularly in categories like Vitamin A, Hem Iron, and Fruits and Vegetables, reflecting improved access to these essential nutrients.

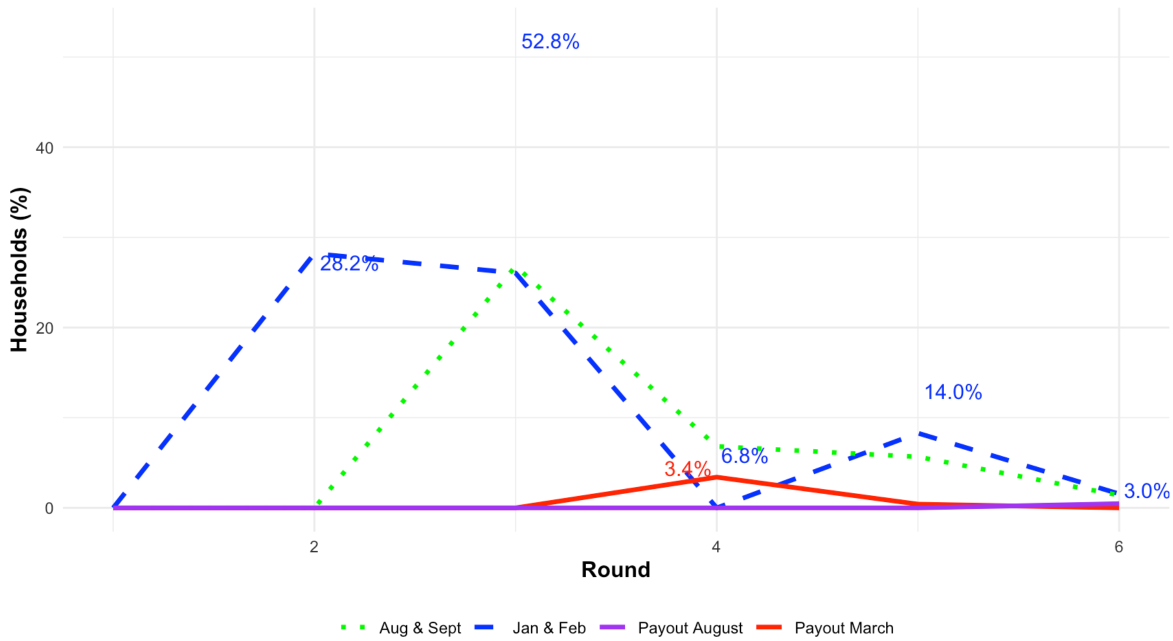
Figure 3: Household food consumption status (FCS)



4.1.3 Insurance Uptake and Payouts

Figure 4 shows a significant peak in insurance sales during Rounds 2 (28%) (2010) and 3(53%) (2011), followed by a drastic decline in demand. Payouts were only made in Rounds 4 (9%) (2013) and 5 (2014) after the 2011/12 droughts. This trend suggests a potential influence of payout experiences on subsequent insurance demand. The concept of basis risk—where payouts from an insurance policy do not perfectly match the actual losses experienced by the policyholder—could explain the fluctuations in demand.

Figure 4: Insurance Uptake and Payouts



The analysis points to the critical role of IBLI in improving food security and nutritional outcomes. However, it also points to the complexities involved in ensuring that insurance products effectively meet the needs of the insured populations. The next chapter reports regression analysis summaries to quantify the impact of IBLI on child nutrition and household food security, providing a more detailed understanding of the relationship.

4.2 Regression results

4.2.1 Effect of IBLI on Child Nutrition Status

Table 1and 2 presents the results from an OLS and IV models which accounts for potential endogeneities. The average MUAC z score is -1.136 ($p < 0.001$), suggesting an overall lower MUAC z-score for children in the sample (table 1). Without controlling for anything, insured households see an increased MUAC z score by 3.6% although it is not significant. Controlling for all unobserved heterogeneity that is constant within each household over time using household fixed effects and unobserved factors that are constant across all households but vary over time using time (round) fixed effects, insurance remains insignificant in all models with coefficients of -0.039, 0.019, -0.081 and -0.040. (models 2,3,4&5).

When age, sex, supplementary food, and TLU class are included (4) with household and time fixed effects, age has a significant negative effect on MUAC z-scores (-0.230, $p < 0.001$), while supplementary food and TLU class (H) (wealthy households) are also significantly negative. Insured households show an insignificant effect at -0.081. Similar to model (4), age, supplementary food, and TLU class (H) remain significant, with the insured household coefficient being -0.040, still insignificant with both household and time fixed effects (5). The gender of the child does not affect their nutrition status (models 4 and 5).

Table 1: Effect of IBLI on child nutrition status (OLS)

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-1.136***				
	(0.021)				
Insured Households	0.036	-0.039	0.019	-0.081	-0.040
	(0.061)	(0.072)	(0.081)	(0.069)	(0.078)
age				-0.230***	-0.224***
				(0.014)	(0.014)
sex				0.055	0.056
				(0.054)	(0.054)
Supplementary food				-0.347***	-0.307***
				(0.054)	(0.055)
TLU class (H)				-0.282***	-0.345***
				(0.072)	(0.082)
TLU class (L)				-0.220	-0.186
				(0.399)	(0.389)
Obs.	3713	3713	3713	3713	3713
R2	0.000	0.358	0.376	0.429	0.438
RMSE	1.23	0.98	0.97	0.93	0.92
FE: hhid		X	X	X	X
FE: round			X		X

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2 reports the results of the Instrumental Variable (IV) regression, which accounts for potential endogeneity in IBLI uptake. The intercept remains significantly negative at -1.161 ($p < 0.001$) (model 1) suggesting an overall malnutrition status of the children in the sample. The coefficient for insured households is 0.237, which is not significant. Including household and time fixed effects (models 2 and 3) changes the coefficient for insured households to 0.191 and -1.683 respectively, while remaining insignificant. Controlling for age, sex, supplementary food, and TLU class with household fixed effects (model 4), the coefficient for insured households is -0.007, still insignificant. Age and supplementary food remain significant with negative coefficients indicating a negative relation between age and receiving supplementary food. Similar to model 4, the coefficient for insured households is -2.189, again not significant when we add time fixed effects (model 5). Age and supplementary food show significant negative effects.

Table 2: Effect of IBLI on child nutrition status (IV)

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-1.161***				
	(0.036)				
Insured households	0.237	0.191	-1.683	-0.007	-2.189
	(0.246)	(0.310)	(2.611)	(0.299)	(2.651)
age				-0.229***	-0.237***
				(0.015)	(0.022)

sex				0.055	0.050
				(0.054)	(0.059)
Supplementary food				-0.350***	-0.375***
				(0.054)	(0.106)
TLU class (H)				-0.208	-2.005
				(0.299)	(2.045)
TLU class (L)				-0.223	-0.366
				(0.398)	(0.584)
Obs.	3713	3713	3713	3713	3713
R2	-0.003	0.356	0.273	0.429	0.277
RMSE	1.23	0.98	1.04	0.93	1.04
FE: hhid		X	X	X	X
FE: round			X		X

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Both OLS and IV estimations indicate that IBLI uptake does not have a significant direct effect on child nutrition status. The coefficients for insured households are not significant across all models, suggesting that although having insurance provides financial security in case of a shock, simply having insurance does not directly translate into improved nutrition outcomes for children in the sample.

The significant negative coefficients for age and supplementary food across both OLS and IV models indicate that older children tend to have lower MUAC z-scores, which could reflect growth patterns and the need for targeted nutrition interventions as children age. The negative impact of supplementary food, though initially counterintuitive, might indicate that households with children receiving supplementary food are those facing more severe food insecurity or nutritional challenges, hence the negative association. The robustness of the negative effects of age and supplementary feeding status, along with the inconsistent and insignificant impact of IBLI, suggests that while insurance may offer financial protection, it does not automatically improve child nutrition.

Table 3 shows that insured households have significantly higher intake levels of several key nutrients: Vitamin A intake is higher by 63.7% (0.637, $p < 0.001$), protein intake by 47%, iron intake by 25%, and intake of fruits and vegetables by 61%. These results indicate a notable improvement in the intake of highly nutritious foods among insured households. However, these significant effects are observed only when controlling for all unobserved heterogeneity that is constant within each household over time using household fixed effects.

When time fixed effects (ρjρj) are added to the model to control for unobserved factors that are constant across all households but vary over time, such as seasonal variations (e.g., drought conditions), economic cycles, or policy changes, the significance of these results disappears. This loss of significance suggests that there were significant improvements in food availability or economic conditions during specific survey rounds that impacted all households equally. These improvements are captured by the time fixed effects, thereby reducing the apparent impact of IBLI uptake. For oil and fat and staple foods, the coefficients for insured households are 0.061 and 0.118

respectively, indicating no robust evidence of an impact on these food groups when household fixed effects are included.

4.2.2 Effect of IBLI on Food Consumption Status

Table 3: Effect of IBLI on Food consumption status (IV)

	Vitamin A		**Protein**		**Hem Iron**		**Oil and fat**		**Staples**		**Fruits and vegetables**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Insured households	0.637***	1.681	0.460***	1.122	0.245***	0.217	-0.061	-0.310	0.111+	0.118	0.611***	0.157
	(0.137)	(1.735)	(0.122)	(1.176)	(0.071)	(0.448)	(0.048)	(0.536)	(0.061)	(0.475)	(0.156)	(1.064)
Obs.	3065	3065	3065	3065	3065	3065	3065	3065	3065	3065	3065	3065
R2	0.231	-1.124	0.272	-0.478	0.696	0.722	0.441	0.215	0.360	0.361	0.565	0.681
RMSE	0.27	0.45	0.23	0.33	0.13	0.12	0.10	0.12	0.13	0.13	0.31	0.27
FE: hhid	X	X	X	X	X	X	X	X	X	X	X	X
FE: round		X		X		X		X		X		X

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4: effect of IBLI on households achieving adequate food consumption.

	Vitamin A	Staples	Fruits and vegetables
(Intercept)	0.007	0.016**	0.001
	(0.005)	(0.006)	(0.002)
Insured households	0.077*	0.068+	0.016
	(0.032)	(0.038)	(0.014)
Obs.	3065	3065	3065
R2	-0.028	-0.013	-0.002
RMSE	0.14	0.16	0.06

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4 further explores the impact of IBLI on achieving adequate nutrient intake. Insured households have a positive and significant coefficient of 0.077 ($p < 0.05$), indicating a 7.7% increased likelihood of achieving adequate Vitamin A intake. The coefficient for insured households is 0.068 ($p < 0.10$), suggesting a marginally significant 6.8% increase in the likelihood of adequate intake of staples. The coefficient for achieving adequate intake of fruits and vegetables is positive but not significant, indicating no strong evidence of an impact.

4.3 Discussion

Both OLS and IV estimations indicate that IBLI uptake does not significantly affect child nutrition status, as the coefficients for insured households are insignificant across all models. Significant negative coefficients for age and supplementary food suggest that older children and those receiving supplementary food face greater nutritional challenges. While insurance improves the intake of Vitamin A, Hem Iron, and fruits and vegetables, it does not robustly impact protein intake or overall nutritional outcomes.

Despite the findings of Tafere et al. (2015, 2018) and Janzen et al. (2013), which suggest that holding an insurance policy improves household well-being by reducing stress about potential adverse outcomes and providing financial stability (Toth et al., 2017), leading to better investment in household welfare, our results indicate that IBLI does not automatically translate to improved nutrition for children. This aligns with the findings of Campbell (1991) and Clark et al. (2009) that addressing food insecurity at the household level is complex, as economic stability does not necessarily result in improved nutrition.

The significant negative relationship between age and supplementary feeding on child nutrition status across both OLS and IV models suggests that older children tend to have lower MUAC z-scores. This is consistent with Venkaiah et al. (2015), who show declining growth patterns and the increasing nutritional needs of children as they age. They further highlight the need for targeted nutritional interventions for older children to ensure they meet their growth requirements, in addition to addressing household risk management.

The negative association between supplementary food and child nutrition status, although initially counterintuitive, might indicate that households with children receiving supplementary food are those already facing more severe food insecurity or nutritional challenges. This aligns with the findings of Rah et al. (2010), which indicate that households receiving food aid or supplementary feeding often do so because they are in worse nutritional status compared to other households. The results, however, suggest that while supplementary feeding programs are crucial to improving the nutritional status of the child, they may not be making substantial improvements over time.

Barrett et al. (2004) and Patel et al. (2019) indicate that households experiencing drought conditions face significant challenges in maintaining food security and dietary intake, which in turn adversely affects child nutrition. Janzen & Carter (2013) and Barrett et al. (2007) further highlight the effectiveness of IBLI as a risk management tool by its ability to reduce economic vulnerability and improve food security among pastoralists. Our findings that IBLI uptake is associated with higher food consumption scores and improved dietary diversity (Vitamin A, protein, iron, and fruits and vegetables) support their arguments and those made by Bageant & Barrett (2015) and Skees & Collier (2008) regarding the utility of microinsurance in stabilizing household economies and promoting better nutritional outcomes. The significant positive effects of IBLI on the intake of Vitamin A, Hem Iron, and staples suggest an increased investment in diverse, nutritious foods, which aligns with the findings of Tafere et al. (2015, 2018) and Janzen et al. (2013), and with Maskooni et al. (2013), who found that socioeconomic status plays a crucial role in dietary intake and food quality.

Furthermore, the study's results indicating the loss of significance when time fixed effects are added suggest that broader economic conditions and seasonal variations play a significant role in influencing household food security and dietary intake. This finding supports the literature, such as Clark et al. (2009), which emphasizes that addressing food insecurity at the household level is complex and affected by multiple factors, and the findings of UNICEF (1990) and Sanfilippo et al. (2012), which highlight the need for integrated approaches combining financial instruments with direct nutritional interventions and food support systems.

In conclusion, despite the positive impacts of IBLI on household food security, IBLI alone does not significantly improve child nutrition outcomes, as indicated by the insignificant effects on MUAC z-scores. This finding aligns with the work of Dercon et al. (2008) and Noritomo et al. (2019), who suggest that while insurance programs are beneficial, they must be complemented by targeted nutritional interventions to effectively address malnutrition.

4.3.1 Limitations

The data used, while robust, may not fully capture the dynamic and complex nature of food security and nutritional outcomes over time. The reliance on Mid-Upper Arm Circumference (MUAC) as a primary indicator has inherent measurement challenges, as it can be influenced by factors such as hydration status and recent illness prior to data collection. Additionally, the findings are specific to Marsabit County, Kenya, which may limit generalizability to other regions with different socio-economic, cultural, and environmental contexts.

4.3.2 Implications for policy and Practice

The findings of this study highlight the need for integrated approaches to effectively address child nutrition and food security in vulnerable regions. While Index-Based Livestock Insurance (IBLI) provides financial stability and enhances household food security, it does not directly translate into improved child nutrition outcomes. Policymakers should consider combining IBLI with targeted nutritional interventions, such as supplementary feeding programs and nutrition education, particularly for older children who face greater nutritional challenges. Enhancing the accessibility and adoption of IBLI through awareness campaigns, subsidies, and educational programs can further stabilize incomes and food consumption, particularly during adverse weather conditions. These integrated efforts can ensure that the financial benefits of IBLI are effectively translated into improved nutritional status for children.

Moreover, the study emphasizes the importance of addressing broader socio-economic factors that influence household food security. Policymakers should design initiatives that provide economic support during lean seasons, improve market access, and enhance agricultural productivity. Strengthening community-level health and nutrition systems, including access to healthcare services and diverse, nutritious foods, is crucial for supporting child health. Continuous monitoring and evaluation of IBLI and associated nutritional interventions are essential to assess their effectiveness and inform policy adjustments. By leveraging these insights, policymakers and practitioners can develop holistic strategies that promote sustainable health and well-being in vulnerable communities, ensuring that financial instruments like IBLI are part of a comprehensive solution to combat malnutrition and food insecurity.

5.0 Conclusion

In summary, this study finds that while the Index-Based Livestock Insurance (IBLI) program has positive impacts on household food security, it does not significantly improve child nutrition outcomes, as measured by MUAC z-scores. Our analysis reveals that older children and those receiving supplementary food face greater nutritional challenges, indicating the need for targeted nutritional interventions. The results align with existing literature suggesting that economic stability through insurance alone is insufficient to address complex nutritional issues. Broader economic conditions, seasonal variations, and existing food insecurity at the household level further complicate the relationship between insurance and nutrition. Therefore, to effectively combat malnutrition, insurance programs must be integrated with direct nutritional interventions and support systems. This comprehensive approach will better address the multifaceted nature of food security and child nutrition, ensuring more robust and sustainable improvements in health outcomes.

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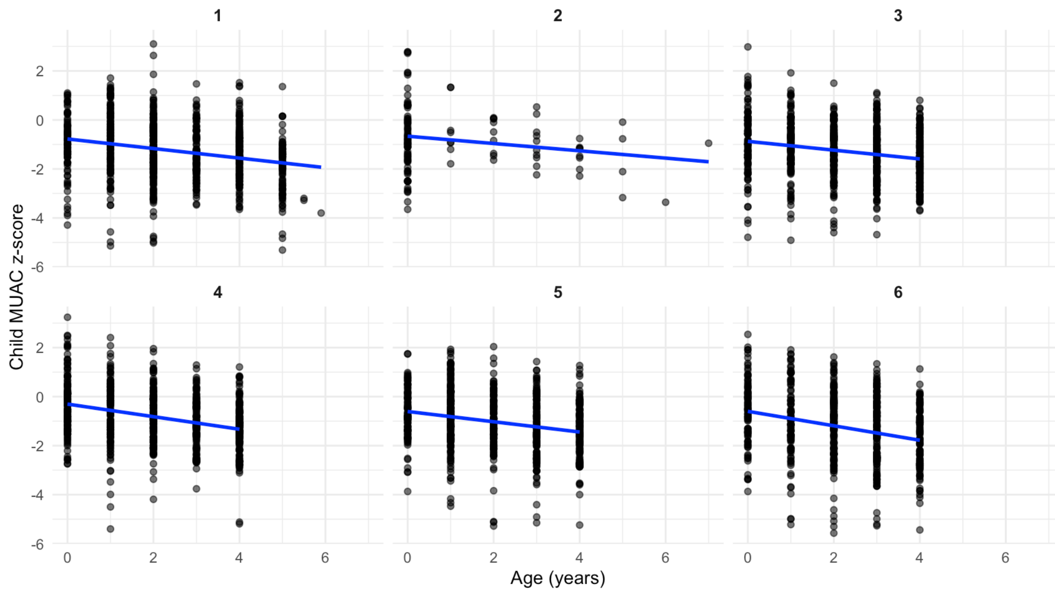
Appendix 1: Children's MUAC Z scores and age



Appendix 2: Dates of household survey rounds, sales, and indemnity payout periods.

Date	Household survey	Firm Selling IBLI in Marsabit District	Index Units with IBLI Payouts
2009: October-November	Round 1		
2010: January-February		UAP	
2011: August-September		Inactive	
2010: October-November	Round 2		
2011: January-February		UAP	
2011: August-September		UAP	
2011: October-November	Round 3		
2011: October-November			Maikona, Central/Gadamoji, Laisamis, Loiyangalani
2012: January-February		Inactive	
2012: March-April			Central/Gadamoji, Laisamis
2012: August-September		APA	
2012: October-November	Round 4		
2013: January-February		APA	
2013: August-September		APA	
2013: October-November	Round 5		
2014: January-February		APA	
2014: March-April			Loiyangalani
2014: August-September		APA	

2015: January-February		APA	
2015: March-April			Maikona, Laisamis (exgratia), Loiyangalani (exgratia)
2015: August-September		APA, TIA	
2015: October-November			Maikona, Loiyangalani
2015: October-November	Round 6		
2016: January-February		APA, TIA	
2016: August-September		APA, TIA	
2017: January-February		APA, TIA	
2017: March-April			Maikona, Central/Gadamoji, Laisamis, Loiyangalani
2017: August-September		TIA	
2017: October-November			Maikona, Central/Gadamoji, Laisamis, Loiyangalani
2018: January-February		TIA	
2018: March-April			Central/Gadamoji, Laisamis
2018: August-September		TIA	
2019: January-February		TIA	

Notes: APA = APA Insurance (https://www.apainsurance.org), TIA = Takaful Insurance of Africa (https://takafulafrica.co.ke)