A PhD dissertation on

Incomes and Asset Poverty Dynamics and Child Health among Pastoralists in Northern Kenya.

By

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2016

Submitted in partial fulfilment of the requirements for the doctorate degree in Economics "Dr. oec. in Economics" to Faculty of Business, Economics and Social Sciences, University of Hohenheim, Germany.

Date of Oral examination: 7th September 2016

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Acknowledgements

Many individuals and organisations have contributed to the successful completion of my studies. Without their support, this work would not have been completed. Special thanks to my supervisor, Prof. Alfonso Sousa-Poza for providing overall guidance for this work. His open and constructive ideas provided insights that helped in shaping the study. I thank him for his patience and effort in reading the various research drafts and instilling in me good research writing skills. I have gained a lot from his leadership and guidance that have broadened my perspective in research. I thank Prof. Christian Ernst for his willingness to co-supervise the thesis. My gratitude also goes to my co-authors Andrew Mude, Steffen Otterbach, Jan Bauer and Micha Kaiser for their contribution while writing the papers. I wish to thank Andrew Mude from ILRI for his valuable support during my study. His time and effort in reading the various drafts is highly appreciated. I thank Patricia Höss for taking care of my travel plans and giving me an office space making my stay in Hohenheim comfortable. I thank Brigitte Kranz for her support in facilitating the numerous workshops and conferences organised by Food Security Center that I attended. I wish also to thank Diba Galgallo, Gideon Jalle, Jan Bauer and the enumerators for their support during the field data collection. Special thanks to German Academic Exchange Service (DAAD) for the PhD scholarship through the Food Security Center (FSC), University of Hohenheim, Germany. I thank Fiat Panis for providing funds to carry out some fieldwork. I wish also to thank Index-Based Livestock Insurance Project (IBLI) in International Livestock Research Institute (ILRI) for allowing me use the household data for my research. Back home, I'm grateful to the prayers, love and support from my family and friends. To my parents Mary Wabia and Paul Mburu, thanks for laying the foundation and your words of encouragement and support throughout my academic life. Sincere gratitude to my wife Peninah Wairimu and our sons Newton Mburu and Brian Kiarie. Thanks for your unwavering love, patience and understanding that was a strong source of motivation throughout the period of study. Special thanks to Peninah for taking care of the family while I was away. Finally to others that I have not mentioned who have contributed to the successful completion of my studies.

To the Almighty God for giving me strength and good health. All the Glory and Honour belongs to Him.

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List of Abbreviations

ASALs	Arid and Semi-Arid areas
DAAD	German Academic Exchange Service
FGD	Focus Group Discussion
FSC	Food Security Center
GDP	Gross Domestic Product
HAZ	Height-for-Age
HSNP	Hunger Safety Net Programme
IBLI	Index-Based Livestock Insurance
ILRI	International Livestock Research Institute
KSH	Kenya Shilling
LOWESS	Locally Weighted Scatterplot Smoother
MNFE	Mobile Non-Formal Education
MUAC	Mid-Upper Arm Circumference
NASA	National Aeronautical and Space Administration
NDVI	Normalized Difference Vegetation Index
NGOs	Non-governmental Organisations
OLS	Ordinary Least Squares
PARIMA	Pastoral Risk Management
PLU	Poverty Line Units
SD	Standard Deviation
TLU	Tropical Livestock Unit
VIF	Variance Inflation Factor
WAZ	Weight-for-Age
WHZ	Weight-for-Height
WHO	World Health Organisation

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General Introduction

The Kenyan drylands, which make up about 84% of Kenya's total land surface, support about eight million Kenyans with animal husbandry as the main source of livelihood. The livestock subsector in these dry areas accounts for over 70% of local family income, as well as 10 % of the country's gross domestic product (GDP) and 50% of its agricultural GDP (Government of Kenya, 2012). Yet despite this sector's significant contribution to the economy, systematic marginalization, poor infrastructure and services, and persistent community conflicts and raids have undermined these dryland areas especially in Northern Kenya. At the same time, the threats from persistent droughts have escalated, with Northern Kenya recording 28 major droughts in the past 100 years and 4 in just the last 10 years (Adow 2008) and in the face of a changing global climate, this trend is likely to continue or even worsen. These recurrent droughts and lack of supporting infrastructure have resulted in increased loss of livestock, leading to income loss that has rendered the pastoralists vulnerable to poverty (Chantarat et al. 2012). This drought volatility follows some cycle from drought to range degradation, loss of animals, restocking of animals followed by the next cycle of drought and recovery (Fafchamps 1998). Households consume livestock products such as milk or slaughter for meat. However, often livestock are sold to provide income for other households needs such as food, school fees and others. Food and cash aid support in these drought prone areas also enables households to cope with the challenge of food shortage. Understanding the sources and changes in incomes and assets as well as poverty levels and the coping strategies in these pastoral areas is necessary to guide policy interventions.

Among pastoralists living in these arid and semi-arid areas (ASALs), the key asset for income, food security, wealth, and social status is livestock (Swift 1986), which researchers therefore use as the primary measure to assess poverty and wealth dynamics within this population. Clearly identifying the levels and shape of household welfare dynamics has important policy implications. For a single dynamic equilibrium, the key question is whether the equilibrium is below or above the poverty line. If above the poverty line, then policy needs to focus on how to support households in maintaining and raising their welfare levels so as to speed up the convergence process. If the equilibrium is below the poverty line, households are likely to be trapped in poverty, implying a need for structural changes that raise household welfare levels. In the presence of multiple equilibria, the household's initial condition matters. If the household starts above (below) the critical threshold, it can be expected to move toward higher (lower) welfare levels. This situation thus requires policy measures that ensure households do not fall below the threshold, especially after adverse shocks. As a critical asset among the pastoralists, the use of livestock to establish welfare dynamics is conceptually convincing. It is also important to find out how shocks such as drought affects household behavior in consumption, labour allocation and accumulation of the herd sizes over time.

Weather-related shocks are a serious global threat that increasingly affect lives across the globe (Stern, 2006). There is strong evidence suggests that weather changes is an important determinant of child health in many developing areas, and undernutrition among children remains common in many parts of the world. Statistics show that during the period 2007-2014, approximately 39.4 % of children under five in the African region were stunted, while 10.3 % were wasted (WHO 2015). In Kenya, children in the arid and semi-arid areas suffer from growth deficiency and are more likely to die at a young age (Government of Kenya 2014a) . The levels of malnutrition is likely to be exacerbated given the more frequent and persistent drought experienced in these areas. While children below five years remain most vulnerable to due to inadequate food intake there is knowledge gap of the effect of drought on child health despite the food support programs that have been going on in the study area.

Investment in childhood education is recognized as one of the basic requirements for economic development. As one of the sustainable development goals by the United Nations it is envisaged that there will be inclusive and quality education for all by 2030 (United Nations 2015). The provision of such formal education to pastoral communities who usually migrate in search of water and grazing pasture, however, is a major challenge, with an estimated global total of nomadic out-of-school children of around 21.8 million (Carr-Hill 2012). In these areas there is the challenge of accessibility to schools with under-investment in schools (Dyer 2013) coupled with insecurity, low population density and harsh physical conditions that create barriers to attracting both learners and adequate number of teachers (McCaffery et al. 2006). In Kenya, the school education curriculum has been designed for children to learn in some permanent locations at a particular time (Krätli and Dyer 2009). This conflicts with the household mobility patterns among pastoralists and partly explains the low school enrolment and completion rates. Since 2003, Government of Kenya introduced universal free primary education that enables children to attend school without paying school fees and other levies. Despite such efforts, however, schools in Kenya's arid and semi-arid districts have recorded lower enrollment and attendance rates than in the rest of the country (Ruto et al. 2010). In this context, therefore, it is important to understand the extent of formal schooling, the effects of herd migration on child schooling and the challenges faced by school children in these marginal areas.

The remainder of the thesis is organized as follows. In chapter one, we carry out a comprehensive and multidimensional poverty analysis using incomes and assets data. We estimate income poverty using imputed household income relative to adjusted poverty line and asset poverty using both asset index based on a regression function and tropical livestock units (TLU) per capita. We further disaggregate both income and asset poverty into structural and stochastic decompositions to show income and asset poverty transitions over time. Methodologically, we seek to compare the tropical livestock units (TLU) approach with a regression-based multidimensional asset index in the estimation of asset poverty in a largely pastoral context.

In chapter two, we explore the livestock asset dynamics. To advance this understanding, we develop a microeconomic model to analyze the impact of a shock (e.g., a drought) on the behavioral decisions of pastoralists. We then explore the livestock asset dynamics using both nonparametric and semi-parametric techniques to establish the shape of the asset accumulation path and to determine whether multiple equilibria exist. We further estimate the household and environmental factors that influence livestock accumulation over time.

In chapter three, we use the child data collected on anthropometric measures to understand the extent of malnutrition for children under five years. We then estimate the effect of weather-related shocks on child health measured using the Mid-Upper Arm Circumference (MUAC Z-scores) while the weather variability estimated using the standardized Normalized Difference Vegetation Index (NDVI Z-scores), which is satellite remote sensing data.

In chapter four we seek to understand the extent of formal schooling by gender and estimate the effects of herd migration on child schooling. We also use some community-level data to shed more light on the challenges facing school-going children in the study area and how they can be addressed. We combine both the household data with Focus Group Discussions to delve more in this research topic. Chapter five presents a summary of the four studies.

Chapter One: Income and asset poverty among pastoralists in Northern Kenya[1]

Abstract

In this study we use household panel data collected in Marsabit district of Northern Kenya, to analyze the patterns of livelihood sources and poverty among pastoralists in that area. We estimate income poverty using imputed household income relative to the adjusted poverty line and asset poverty using a regression-based asset index and tropical livestock units (TLU) per capita. Our results indicate that keeping livestock is still the pastoralists' main source of livelihood, although there is a notable trend of increasing livelihood diversification, especially among livestock-poor households. The majority of households (over 70%) are both income and livestock poor with few having escaped poverty within the five-year study period. Disaggregating income and asset poverty also reveals an increasing trend of both structurally poor and stochastically nonpoor households. The findings show that the TLU-based asset poverty is a more appropriate measure of asset poverty in a pastoral setting.

Keywords: livestock, asset index, poverty, pastoralists, Kenya

1.0 Introduction

The Kenyan drylands, which make up to 84% of Kenya's total land surface, support about eight million Kenyans with animal husbandry as the main source of livelihood. The livestock subsector in these dry areas accounts for over 70% of local family income, as well as 10% of the country's gross domestic product (GDP) and 50% of its agricultural GDP (Government of Kenya, 2012). Yet despite this sector's significant contribution to the economy, systematic marginalization, poor infrastructure and services, and persistent community conflicts and raids have undermined these dryland areas, especially in Northern Kenya. At the same time, the threats from persistent droughts have escalated, with Northern Kenya recording 28 major droughts in the

[1] This article is printed with permission from Taylor & Francis Group. It was published in the Journal of Development Studies. It is available online: *http://dx.doi.org/10.1080/00220388.2016.1219346*

past 100 years and four in just the last 10 years (Adow, 2008), and given the changing global climate, this trend is likely to continue or even worsen. These recurrent droughts and lack of supporting infrastructure have resulted in increased loss of livestock, leading to income loss that has rendered the pastoralists vulnerable to poverty (Chantarat et al., 2012). Whereas households primarily consume livestock products like milk or slaughter animals for meat, they also frequently sell livestock to provide income for other household needs such as food, school fees, and other necessities. Food and cash aid support in these drought prone areas also enables them to cope with the challenge of food shortage.

Although understanding the extent and nature of poverty and income sources in these pastoralist communities is important for the design of appropriate developmental policies, a lack of adequate data has limited such analyzes to only a handful. Among these, Berhanu et al. (2007) show that external shocks such as persistent drought have driven the Borana pastoralists of Southern Ethiopia to diversify their livelihoods to nonpastoral activities such as arable farming, even though pastoralism is still their main form of self-support. Little et al. (2008) further demonstrate that the severe poverty in pastoral areas is more prevalent among sedentary ex-pastoralists than among mobile pastoralists who generally have more livestock, primarily because the limited nonpastoral livelihood options available in these areas ensure the latter lower incomes than the former. Pedersen and Benjaminsen (2008) similarly argue that in arid environments, nomadic pastoralism is a better form of livelihood than sedentary farming because the time costs of combining both forms are high.

In this study, we take advantage of unique panel data on the livelihood sources, incomes, livestock owned and household characteristics of pastoralists in Northern Kenya to conduct a more comprehensive and multidimensional poverty analysis than previously possible. These data enable a more thorough investigation of both the pastoralists' household incomes and their asset poverty and the manner by which these two measures of welfare provide different insights into household wealth and the dynamics of poverty. The study thus has three main objectives: to establish the levels, sources, and trends of household incomes across five survey waves, to estimate and compare income and asset poverty levels, and to identify systematic variations in welfare insights that can be drawn from the application of different income and asset poverty metrics to the same data. Thus, this study contributes to the literature in a number of ways: first, it is one of the few studies that takes a look at both income and asset poverty among pastoralists using household panel data. Second, we compare the tropical livestock units (TLU) approach with a regression-based multidimensional asset index in the estimation of asset poverty in a largely pastoral context. Finally, we show how the households diversify their income sources as herd sizes decrease over time.

The application and comparison of both an asset-based and income-based welfare metric is particularly novel. Furthermore, such an application and comparison is important in contexts similar to our study area where livestock assets are both the principle source of income and the key productive asset. The findings from this study indicate that the TLU-based asset poverty measure describes welfare and its dynamics more appropriately in a pastoral set-up. The study also shows that a large majority of the households are both income and asset poor, implying that they do not have sufficient assets to exit poverty. Furthermore, it also shows that livestock poor households have more diversified income portfolios than those with more livestock. As such, where assets are low, or comprise a smaller share of household wealth and income, income-based measures of wealth may become better predictor of household wellbeing.

1.1 Measuring Asset-Based Poverty

Several poverty analyses (Adato et al., 2006; Brandolini et al., 2010; Grosh and Glewwe, 2000) emphasize the importance of household net worth (assets) in maintaining well-being, especially when income is unstable. Such assets implicitly contain information on future livelihood, cushion against income shocks, and act as a source of future income and consumption streams (Brandolini et al., 2010; Mckay, 2009).

Combining both asset and income poverty measures produces four classifications: (i) the structurally poor (income poor and asset poor), (ii) the stochastically poor (income poor but asset nonpoor), (iii) the stochastically nonpoor (income nonpoor but asset poor), and (iv) the structurally nonpoor (income nonpoor and asset nonpoor) (Paxton 2013). Most current research using asset-based approaches adopts either a one-dimensional asset measurement justified by its predominance in the region (e.g., livestock) or use a combination of assets to generate an asset index.

Methodologies similar to ours are employed in one study by Little et al. (2008) who focus on pastoralists, and other work by Radeny et al. (2012) and Liverpool-Tasie and Winter-Nelson (2011), who focus on households practicing both crop and livestock farming. Radeny et al. (2012) combine event histories with panel survey data collected by the Tegemeo Institute from 1,500 households in different agro-ecological zones across 24 Kenyan districts to identify trends in rural poverty dynamics over the 2000–2009 period. By applying an asset-based approach to distinguish stochastic from structural poverty across the survey period, they demonstrate substantial movement across the various poverty categories with only a few households escaping poverty through asset accumulation.

A similar study by Liverpool-Tasie and Winter-Nelson (2011) estimates asset and expenditure-based poverty using 1994–2004 panel data from the Ethiopian Rural Household Survey (ERHS), which covers 1,477 households representing 15 administrations across four regions. After first compiling an asset index by estimating the relation between assets and expenditure, the authors use it to categorize households into various poverty categories based on asset poverty lines. Their comparison of asset-based and income poverty reveals that income poverty measures identify more households (56%) as having moved out of poverty between 1994 and 2004 than do asset-based measures (19%) suggesting that the former are more stable because they reflect structural rather than stochastic causes, which may only be temporal.

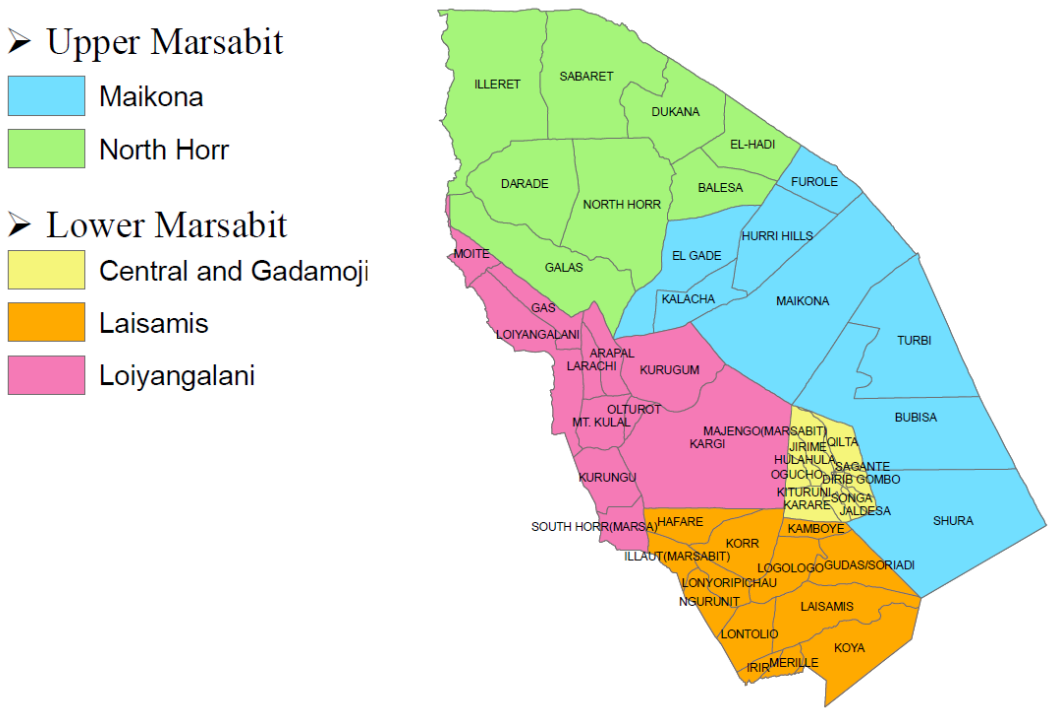
Little et al. (2008) analyze pastoral poverty in the East African region based on household data from a survey conducted in Northern Kenya and Southern Ethiopia by Pastoral Risk Management (PARIMA) between 2000 and 2006. To estimate poverty, the authors use a TLU per capita threshold, which they argue can distinguish welfare and livelihood strategies at 4.5+TLU per capita, thereby dividing better-off households from poor households. More specifically, households with livestock below the 4.5+TLU level are unable to escape poverty even during good times when grazing pastures are adequate. They note that although livestock husbandry is the main core economic activity and contributes the largest share of household income before food aid, the households' economic activities show considerable diversification. Their results also reveal that food transfers are more common among the poorest households, whereas livestock production is most important for the middle and upper income households in terms of both shares and levels. This finding echoes Mcpeak and Barrett's (2001) observation of a positive relation between household per capita income and herd size. Little et al. (2008) also find that because the opportunities for non-pastoral economic activities are limited, active pastoralists are more likely to enjoy increased levels of household income and are less poor than settled pastoralists are.

Overall, asset-based poverty measures can yield a more robust profile of poverty, especially when applied to panel data. Hence, to fill the research gap on poverty among pastoralists, this present study, unlike most reviewed here, employs panel data collected from pastoral households over five consecutive years. Likewise, rather than adopting a single measure to estimate asset poverty as is common in the research stream, it implements two approaches (based on an asset index and a TLU per capita threshold).

1.2 Study Area and Data

1.2.1 Study Area

Marsabit district is characterized by an arid or semi-arid climate (rainfall of up to 200mm/year in the lowlands and 800mm/year in the highlands), droughts, poor infrastructure, remote settlements, low market access, and low population density (about four inhabitants per km^2). This area, which covers about 12% of the national territory, is home to about 0.75% of the Kenyan population and encompasses several ethnicities — including Samburu, Rendille, Boran, Gabra, and Somali — each with distinct languages, cultures, and customs. These pastoral communities live in semi-nomadic settlements in which livestock, the main source of livelihood, is moved across vast distances in search of grazing pastures, especially during the dry season. Largely dependent on milk from livestock (mainly camels or cattle) for home consumption, these communities also trade or sell animals (primarily goats and sheep) to purchase food and other commodities (Fratkin et al., 2005).



Source: IBLI web site http://ibli.ilri.org

Figure 1 Study area in Marsabit District

1.2.2 Data

Our panel data are the result of the International Livestock Research Institute's (ILRI) Index-Based Livestock Insurance (IBLI) project, which, beginning in 2009, annually surveyed 924 households living in the Marsabit district of Northern Kenya, with follow-ups conducted until the latest survey wave in 2013. Information was collected in 16 sublocations[2] (see Figure 1) using a sample that was proportionally stratified on the basis of the 1999 household population census. There were only two exceptions to this rule: a minimum sample size of 30 households and maximum of 100 households per sub-location. The households were classified into three wealth categories based on livestock holdings converted into TLUs[3]; low (<10 TLU), medium (between 10 and 20 TLU), and high (>20 TLU). Within each sublocation, one third of the location-specific sample was randomly selected from each of these wealth categories, which were then used to randomly generate a list of households. For replacement purposes, additional households were randomly selected based on the wealth class that were to be used in case a household was to be replaced. For example, if a low, medium, or high wealth household could not successfully be re-interviewed, it was replaced by an equivalent household during subsequent surveys, yielding a consistent sample of 924 households across all five survey waves.

1.3 Methodology

The IBLI data provide a wealth of information on household composition and demography, household livestock accounting (including livestock holdings, sales, and production), livelihood activities, and sources of income. They also include rich information on formal and informal cash and in-kind transfers, including food aid, school meals, and supplementary feeding programs. The fact that these variables are recorded by season enables differentiation between dry and rainy

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[2] The 16 sublocations are Dirib Gombo, Sagante, Dakabaricha, Kargi, Kurkum, Elgathe, Kalacha, Bubisa, Turbi, Ngurunit, Illaut, South Horr, Lontolio, Loyangalani, Logologo and Karare.

[3] The TLUs help to quantify the different livestock types in a standardized manner. Under resource driven grazing conditions, the average feed intake among species is quite similar, about 1.25 times the maintenance requirements (1 for maintenance, and 0.25 for production; i.e., growth, reproduction, milk). Metabolic weight is thus considered the best unit for aggregating animals from different species, whether for the total amount of feed consumed, manure produced, or product produced. The standard used for one tropical livestock unit is one cow with a body weight of 250 kg (Heady 1975), so that 1 TLU = 1 head of cattle, 0.7 of a camel, or 10 sheep or goats.

season data, which is particularly relevant for local price changes.[4] We are thus able to use income rather than expenditure as our poverty indicator, thereby avoiding the measurement errors stemming from householders' tendency to overestimate expenditure (Glewwe and Nguyen 2002). However, income is often underestimated. We derive our aggregated incomes from various income components consistently collected in several survey rounds and although we cannot ascertain the extent of income underestimation, the incomes seem sufficiently reliable across the years. A comparison of income versus expenditure has mostly failed to confirm the superiority of either measure over the other (Deaton, 1997), particularly in assessing long-term welfare, yet detailed collection and comprehensive consideration of various income components tends to produce reliable income data (Radeny et al., 2012).

We therefore analyze income, its change over time, and the contribution made to total household income using the following three components: (i) farm income (livestock sale, value of slaughtered livestock, value of milk and crop production net of livestock input cost); (ii) nonfarm income (regular labor income, casual income from day labor activities, cash income from small business activities like charcoal selling or operating small shops, and the value of net transfers, both cash and in-kind, from family members); and (iii) assistance from nongovernmental organizations (NGOs), government, and other institutions (cash aid, food aid, school meal programs and supplementary meals expressed in monetary terms). We include these types of assistance because they are important to the households' overall welfare. Although the values of these income components are admittedly based on self-reports, the median unit prices by animal type (camel, cattle, sheep or goat) and by season are calculated and multiplied by the quantities of livestock sold. Likewise, the value of milk produced is calculated using a median

[4] Typical climate conditions over the course of the year include a short (January–February) and long (June–September) dry season and two rainy seasons (March–May, also known as the long rainy season, and October–December, also known as the short rainy season).

unit price by animal type and season (for those households that actually sell milk) multiplied by the quantities produced. In this way, we account for the large variation and extreme values typical of self-reports, as well as the seasonal variation in prices for the two main income components.

We aggregate these income components on the household level (livestock, salaries, business and net cash and in-kind transfers) and calculate monthly per capita income. To categorize whether a household is income poor, we use the absolute and official overall 2006 poverty line of 1,562 Kenyan shillings (Ksh) per month for rural areas, which is based on the Kenya Integrated Household Budget Survey 2005/2006 (KNBS, 2007).[5] To account for inflation, we adjust the 2006 poverty line using average annual inflation rates for 2007 to 2013 (see appendix 1). We also use monthly per capita income and inflation-adjusted poverty lines to calculate a poverty headcount index, a poverty gap index, and a poverty severity index based on the Foster-Greer-Thorbecke measures (Foster et al., 1984).

Comparing household income with the national poverty line, however, tells only half the story: because income can exhibit fluctuations, a poverty analysis based solely on income does not take into account household endowments and assets. Moreover, in a pastoralist setting, poverty measures based on either income or expenditures can be misleading because pastoral production involves mobility, which limits the amount spent on consumables. It also provides little information on investments in substantive assets, meaning that indicators such as income or expenditures do not fully depict pastoral poverty. We therefore complement the income measures with an asset-based approach to poverty analysis, which assumes that economic well-being depends on endowment and ownership of or access to productive assets. Using an asset index has the advantage that assets are less volatile than income and less prone to random shocks. Asset data are also considered more accurate than income data because respondents can recall the

[5] The official poverty line is also used by Radeny et al. (2012), Suri et al.(2009) and Barrett et al. (2006).

quantities of assets they own better than their income or expenditures. Moreover, a combination of income and asset-based poverty measures enables us to classify households into the four categories previously defined, which are illustrated in Figure 2: (i) structurally poor (region A), (ii) stochastically poor (region B), (iii) stochastically nonpoor (region C), and (iv) structurally nonpoor (region D).

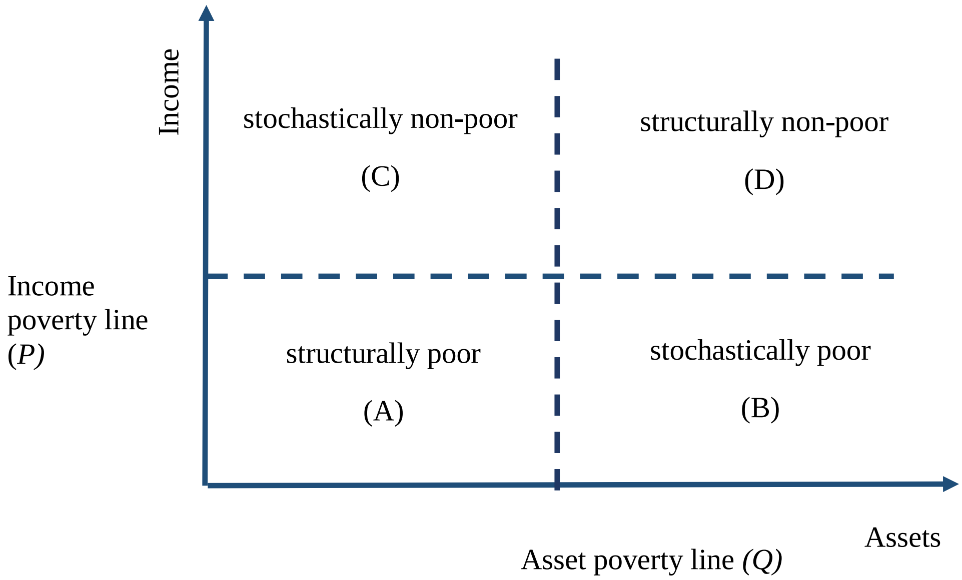

Figure 2 Income and asset poverty

Here, the asset poverty line $\boldsymbol{Q}$ indicates the level of assets that predicts the level of household well-being given by the income poverty line $\boldsymbol{P}$. At any given period, a household is structurally poor if its income is below $\boldsymbol{P}$ and its assets stocks are less than $\boldsymbol{Q}$. Movement from $\boldsymbol{D}$ to $\boldsymbol{A}$ reflects a structural transition to below the poverty line because of a loss of or decreased returns on assets that causes income to fall this low. In general, movement in the opposite direction (from $\boldsymbol{A}$ to $\boldsymbol{D}$**)** represents a structural shift out of poverty, possibly because of either an accumulation of assets or improved returns on the household's existing assets (Carter and Barrett, 2006; Barrett et al., 2006).

Because establishing these poverty decompositions requires that assets and income be mapped, we follow (Adato et al. 2006) in estimating the following asset index;

$$L_{it} = \alpha + \beta A_{it} + \gamma H_{it} + \delta T_t + \omega S_i + \varepsilon_{it} \quad (1)$$

where L_{it} denotes household *i*´s aggregate monthly income per capita at time *t* divided by the adjusted poverty line, and A_{it} is a set of assets; namely, livestock in the form of camels, cattle, sheep, and goats expressed in TLUs. Other physical assets include ownership of a phone and radio expressed as dummies. We also include membership in a group as a proxy for social capital. Not only are livestock expected to have a positive effect as a direct source of income, but other assets are anticipated to make a positive contribution to the household's productive capacity and hence also increase income. H_{it} is a set of household characteristics, including the gender, age, and education of the household head. Male-headed households are expected to be better off than female-headed households are because a household supported by both spouses is expected to generate more income. We also include the number of children under 15 years, the number of adults aged between 15 and 65, and the number of older adults over 65 years. Households with a high number of dependent members (young and old) are expected to show a negative effect since these member's contribution to household income is limited.

The equation also includes T_t, a set of time dummy variables, S_i, sublocation dummies, and ε_{it}, the error term. We then estimate a fixed effects model whose linear prediction of L_{it} yields the asset index,[6] meaning that $0 \leq \hat{L}_{it} \leq 1$ and $\hat{L}_{it} > 1$ indicate whether a household is poor or nonpoor, respectively, in terms of assets. It is worth noting that we use a relatively parsimonious specification in order to calculate the asset index. In essence, we focus on livestock, the main productive asset, and include a few assets related to human capital and physical assets. Other studies that focus more on mixed farming (Giesbert and Schindler, 2012; Liverpool-Tasie and

[6] We also estimate the asset index using a random effects and pooled OLS model. However, the Breusch-Pagan Lagrange multiplier test and the Hausman test both indicate that the random effects model is superior to the pooled OLS model and the fixed effects model superior to the random effects model, respectively.

Winter-Nelson, 2011; Adato et al., 2006) use a much wider set of assets, including land owned, farm equipment and geographic capital (for example distance to the social amenities). Because of their nomadic way of life, the sampled households possess few of these assets: land is largely communally owned, so the vast majority of households own none. According to the data, only a few households (less than 10%) sell milk, suggesting that the bulk of the milk produced is for home consumption. Furthermore, because the infrastructure in the area is poor, there are no well-developed milk markets, so households sell milk mostly to their neighbors.

We therefore employ an alternate measure to estimate asset poverty and distinguish asset poor from nonpoor households, namely the 4.5TLU per capita threshold already documented as accurately identifying pastoral households prone to poverty even during periods of adequate grazing (Lybbert et al. 2004; Little et al. 2008). This use of herd size to distinguish between poor and nonpoor is validated by research findings that, in arid and semi-arid areas, households hold livestock for their relatively high expected returns (albeit matched by high variability), as well as the insurance they provide against future income shocks (Dercon and Krishnan, 1998; Desta et al., 1999).

1.4 Descriptive Statistics

In Table 1, we report descriptive statistics for the households pooled over all five survey waves. The average livestock owned in TLUs is equal to 6.7 camels, 3.1 cattle, and 3.9 sheep or goats, which is equivalent to an average of 9 camels, 3.1 cows, and 39 sheep or goats. These figures indicate an average household size of 5.9 members, with a household head aged on average 49 years and 62% likely to be a male. Households in the sample are quite poor, with mean real monthly income per capita of 1,940 Kenyan shillings. The ownership of mobile phones, however, has been on the increase with on average 40% of the households owning at least one.

Table 1 Summary Statistics

Variable	Mean	SD	Mean difference between (2013-2009) [c]
Camel in TLUs	6.7	12.9	-0.74*
Cattle in TLUs	3.2	6.9	-1.65***
Shoats in TLUs	4.0	5.9	-1.05***
TLU per capita	2.6	4.1	-0.97***
Household size	5.9	2.4	0.79***
Household head (male)	62.0%	0.5	-0.005
Age of head	48.8	17.2	2.85***
Education of head (1=yes)	11.4%	0.3	0.03***
Belong to a group (1=yes)	9.7%	0.3	0.04*
Monthly real income per capita (Ksh)	1,940.5	2,888.1	752.20***
Own a radio (%)	25.2%	0.4	0.06***
Own a phone (%)	40.1%	0.5	0.23***
Relative income[a]	0.9	1.3	0.01
Asset index[b]	0.9	0.6	0.01

Notes: [a] Relative income is monthly per capita income divided by the adjusted income poverty line
[b] Asset index is the predicted household income relative to the poverty line derived from a household's productive assets
[c]T-test with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The statistics are based on pooled data of 4,518 households

The mean difference between 2009 and 2013 for most of the variables is statistically significant, which implies substantial changes in these variables between the two periods. The major source of income across all survey years is livestock, derived from the value of milk produced, livestock sales, and/or the value of slaughtered animals (see Table 2). Milk value accounts for the highest share of livestock income in the 2009–2013 period, although there is a drop in milk income in 2010 that may be attributable to a drop in milk production during the 2009 drought year. Moreover, the share of milk income decreases across the period from 86% in 2009 to 75% in 2013.

Table 2 Livestock real income values in (Ksh)

Income component	2009	2010	2011	2012	2013
Livestock sold	7,635.2	12,144.5	19,446.5	23,287.9	25,884.4
Value of milk produced	71,992.0	58,888.4	71,128.9	71,697.4	97,120.7
Livestock slaughtered	4,038.4	885.4	5,221.9	6,415.9	6,916.4

Note: Ksh=Kenya Shilling

The declining milk income is consistent with the gradual decrease in the number of lactating animals shown in Table 3. Milk produced per animal per day also declines in the 2009-2010 period mainly due to drought effects. There is also a notable increase in real milk prices with the median price of camel milk almost doubling from Ksh 36.2 per liter in 2009 to Ksh 69.1 per liter in 2013 and the price of cow and sheep/goat milk from Ksh 31.7 to Ksh 69.1 and from Ksh 32.6 to Ksh 75.7 per liter, respectively, in the same period.

Table 3 Mean number of lactating animals and milk produced per day

Average lactating animals	2009	2010	2011	2012	2013
Camel	3.4	2.2	2.1	2.0	2.5
Cattle	3.9	2.3	2.1	2.0	2.1
Goat/sheep	10.5	7.9	5.5	5.1	5.6
Milk produced per animal per day in litres					
Camel	4.4	2.5	2.4	1.8	3.0
Cattle	3.8	1.9	1.7	1.9	2.0
Goat/sheep	3.9	3.1	2.9	2.5	2.1
Median milk price in Ksh per litre					
Camel	36.2	44.2	70.2	54.8	69.1
Cattle	31.7	38.4	43.9	73.1	69.1
Goat/sheep	32.6	48.0	52.6	73.1	75.7

During the same period, income from livestock offtake (including the sale of livestock and the use of animals to pay off debt) increases threefold even though we exclude offtake transactions like animal exchange, gifting, or loaning, which earn no income for the households. Households mostly sell livestock for regular cash income (44.6%), to cope with drought (41.9%), and/or to pay for school fees (8.8%). As Table 4 shows, the mean sales of camels, cattle, and goats/sheep vary little across the years, with the highest mean sale prices reported in 2011, a drought year. On the other hand, the average real livestock prices increase substantially, with camel prices more than doubling and cattle, sheep, and goat prices increasing over fourfold between 2009 and 2013. Even so, the number of livestock sold remains low, implying households' reluctance to sell their animals despite increasing prices.

Table 4 Mean number of livestock sold and average real prices

Average livestock sold	2009	2010	2011	2012	2013
Camel	1.4	1.4	1.8	1.4	1.3
Cattle	1.9	2.0	2.0	1.7	1.4
Goat/sheep	5.1	4.0	6.2	3.4	3.2
Number slaughtered					
Camel	1.1	1.0	1.2	1.1	1.0
Cattle	2.0	1.6	2.2	1.0	1.3
Goat/sheep	3.4	1.5	2.3	1.6	1.5
Average price in Ksh per animal					
Camel	11,141	16,480	20,961	25,372	33,483
Cattle	6,091	10,960	11,676	18,126	22,484
Goat/sheep	570	1,174	1,920	2,871	2,981

No doubt the multiple purposes that livestock serve among pastoralists influence the owners' offtake responses to high prices. Not only are livestock a source of wealth and a means of social insurance, but when slaughtered for home consumption or sold to buy other food items, they also play an important role in smoothing household consumption during drought periods. Indeed, the importance of livestock as a source of wealth is manifested by their crucial role in cultural practices like inheritance and marriage. It is also notable that the number of slaughtered animals is highest for 2011 (a drought year), perhaps to provide food for the family and avoid further losses from the dying animals. The mean income values and proportions from different income sources are outlined in Table 5.

Table 5 Real income values (Ksh) and shares of total household income

Income source	2009		2010		2011		2012		2013	
Income	Ksh	%	Ksh	%	Ksh	%	Ksh	%	Ksh	%
Livestock	81,523	72.7	70,993	77.7	94,072	72.3	99,013	64.7	127,101	71.9
Business	8,526	7.6	9,589	10.5	8,579	6.6	16,735	10.9	13,600	7.7
Casual labor	2,948	2.6	706	0.8	3,551	2.7	6,809	4.4	8,224	4.7
Salary income	13,649	12.2	4,447	4.9	14,334	11.0	21,565	14.1	20,814	11.8
Cash aid	1,050	0.9	2,120	2.3	1,839	1.4	2,229	1.5	1,181	0.7
Food aid	1,743	1.6	874	1.0	5,582	4.3	1,810	1.2	778	0.4
Net transfers	1,317	1.2	738	0.8	485	0.4	2,069	1.4	1,701	1.0
Crop income	1,021	0.9	1,925	2.1	1,073	0.8	2,313	1.5	2,890	1.6
Total income	112,066		91,392		130,086		153,048		176,846	

Notes: The statistics are based on data for the 924 households in each year. Ksh= Kenya Shilling

According to Table 5, although livestock is the main source of income across the survey periods, the households experienced a consistent increase in salaried, business, and casual income that could imply household diversification of income sources away from livestock. Salaried income, which ranks highest, includes positions such as civil servants/government officials (23.8%), security guards (22.4%), and teachers/education officers (20.9%), while business income is mainly from petty trading in charcoal, water, or other basic commodities (62.1%), shop keeping (17.8%), or selling alcohol/cooked food and beverages (6.9%). Casual labor includes temporary off-farm jobs (48.7%), farm labor (20.8%), and herding for pay (12.5%).

Net cash and in-kind transfers, which include remittances and clothes or other assistance from relatives, neighbors, and friends, vary little across the study period. Likewise, the main crops sold are consistently maize (30.8%), khat (28.8%), and beans (13.2%). Food aid is also common across the sampled households, offered mainly through the government or nongovernmental organizations that provide rationed cereals and food supplements for young children. Households also benefit from the government sponsored school meals program for primary school children in selected regions that are prone to drought and hunger. Selected vulnerable households also receive aid from the Hunger Safety Net Program (HSNP), which distributes cash transfers of approximately Ksh 4,200 every two months[7] through appointed agents (for example shopkeepers and NGO staff) in the area. As expected, crop income is low because most regions in the study area do not support rain fed crop farming, so less than 5% of the sampled households engage in crop farming.[8]

In terms of income proportions, livestock income consistently accounts for the largest share of household income, averaging 72% by 2013. Overall, shares from off-farm income remain stable

[7] The frequency and amount of the money given to the beneficiary households have changed over time.

[8] The few households who engage in crop farming are located primarily in four sublocations: Dakabaricha, Dirib Gombo, Sagante, and South Horr.

over the five-year period, while incomes from net transfers reduce marginally. The results for food aid, which comprises the value of food received, supplementary food provision, and school meals, indicate increased assistance to households (4.3%) in 2011, which can be attributed to the 2011 drought that prompted a high level of response from the government and other food relief agencies. Additional analysis also shows that the contribution of salary and business incomes to the household income is higher in educated than uneducated households.[9]

1.5 Income and Asset Poverty

1.5.1 Income poverty

We explore income poverty trends by computing the Foster-Greer-Thorbecke (FGT) indices as reported in Table 6. According to the poverty headcount ratio, the majority of the households are income poor, with the highest average headcount of 79.9% occurring in 2010 and an overall marginal decline in income poverty from 72.6 % in 2009 to 70.9 % in 2013. The results also reveal that the majority of households are income poor across the entire five-year period, with only a few reporting incomes above the poverty line. One limitation of the headcount ratio, however, is that it ignores the depth of poverty; that is, even if the poor become poorer, the headcount index does not change. The poverty gap ratio, in contrast, estimates the depth of poverty by considering how far, on average, the poor are from the poverty line. These results indicate a consistent decline in the poverty gap from 46.6% in 2009 to 36.7% in 2013, suggesting that even though the income poor may not be out of poverty yet, they are becoming better off. A similar decline is observable

[9] To establish the factors that could influence income diversification, we compute the inverse of the Herfindahl index (H), which measures the degree of concentration of household income into various income sources. This inverse is defined as $H = \sum_{k=1}^{n}\left(\frac{1}{(s_k)^2}\right)$, where S is the share of income of source k. Households with more diversified income sources have the largest index, while households with one income source have an index equal to one. We also calculate the correlation coefficients between the index and several household variables: the household size variable is positive and significant, while education is negative and significant, indicating that educated households have fewer income generating activities.

for the poverty severity index, which measures the gap between the poverty line and the average income of the poor, with larger values signaling deeper income poverty.

Table 6 Poverty trends in Marsabit, 2009–2013

Poverty indicator (%)	2009	2010	2011	2012	2013
Headcount ratio (α = 0)	72.6	79.9	71.5	75.5	70.9
Poverty gap ratio (α = 1)	46.6	54.8	45.2	42.6	36.7
Poverty severity index (α = 2)	35.2	44.1	33.8	28.8	23.9

Note: The FGT measure, P(α) is define as $(\alpha) = \frac{1}{N}\sum_{i=1}^{N}\left(\left(\frac{z-y_i}{z}\right)^{\alpha}\right) I(y_i < z)$ where N is the population size, y_i is level of income welfare of the i*th* household, z is the income poverty line, I (.) is a function with a value of one when the constraint is satisfied and zero otherwise. α is a measure of the sensitivity of the index to poverty and the poverty lines.

1.5.2 Asset poverty based on the asset index

The fixed effects regression function used to derive the asset index is depicted in Table 7, in which the coefficients on livestock (measured as the TLUs for cattle, camels, and sheep/goats) are all as expected positive and significant. Ownership of a phone and radio are positive but not significant, while group membership is negative and insignificant. The effect of education on income is positive but not significant, which is barely surprising given the levels of human capital in this pastoralist setting: the most educated household heads have only about one year of schooling and over 80% of household heads are illiterate. The different age categories, in contrast, are all negative and significant for both children and adults under 65, indicating that irrespective of age, most members do not contribute significantly to household income.[10] The dummy variable for survey wave is positive and significant except in wave two, which implies that income improved in all subsequent waves except this one.

[10] Using the dependency ratio instead of the three different age categories still yields a similar negative and significant estimate.

Table 7 Asset index model estimates

Dependent variable: Relative income	Fixed effect
Camels (TLU)	0.0144***
	(0.002)
Cattle (TLU)	0.0053*
	(0.004)
Shoats (TLU)	0.0386***
	(0.005)
Own radio (1=yes)	0.0189
	(0.136)
Own phone (1=yes)	0.0061
	(0.076)
Belong to a self-help group (1=yes)	-0.0220
	(0.059)
Household gender (1=male)	-0.0504
	(0.171)
Age of head	0.0053
	(0.004)
Education of head (1=yes)	0.0797
	(0.223)
Number of children under 15 years	-0.1271***
	(0.025)
Number of adults 15–65 years	-0.0974***
	(0.027)
Number of adults over 65 years	-0.0940
	(0.085)
Constant	1.3462***
	(0.262)
N	4518
adj. R^2	0.182

Note: Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Time and sub-location dummies estimated but not shown

The main objective of this regression is to derive weights that reliably predict expected incomes given a set of productive assets. Because the asset index is made up of the values of relative income predicted from the estimated coefficients, the static asset poverty line corresponds to an asset index value of one. Households with a value greater than one are considered asset nonpoor, while households with a value less than one are considered asset poor. The shares of asset poor versus asset nonpoor households across the survey periods are reported in Table 8 (panel A).

Table 8 Asset index poverty in percentages by survey period

	2009	2010	2011	2012	2013
Panel A: Asset index poverty					
Poor	58.5	75.0	56.3	63.7	56.7
Nonpoor	41.5	25.0	43.7	36.3	43.3
Panel B: TLU poverty					
Poor	79.9	77.9	85.6	89.9	88.6
Nonpoor	20.1	22.1	14.4	10.1	11.4

Note: The statistics are based on data for the 924 households in each year. TLU poverty is based on the 4.5+ TLU per capita threshold

As Table 8 panel A illustrates, a majority of households remain asset poor over the survey period, with relatively low average asset index values in 2010 and 2012 (0.66 and 0.85, respectively), resulting in lower expected incomes compared to other periods. The high rate of asset poverty in 2010 (75%) could be attributed to low milk productivity resulting in depressed livestock incomes (see Tables 2 and 3). We also note a reduction in the proportion of the poor between 2010 and 2011, as well as between 2012 and 2013, which can be attributable to improved returns from the productive assets in this period.

The TLU-based asset poverty measure shows (see Table 8, panel B) that the majority of households are livestock poor (own less than 4.5 TLU per capita). Whereas the number of nonpoor households decreases from 20.1% in 2009 to 11.4% in 2013, the share of livestock poor households increases from 79.9% to 88.6% across the same period, a rise consistent with the declining trend in livestock ownership. These results clearly indicate that the households have not managed to recover from the huge livestock losses incurred in the 2011 drought.

The percentage contributions of different income sources to households with different livestock endowments (see Table 9) further suggest that livestock poor households depend more on different sources of livelihood than better-off households. Households with less than or equal to 1 TLU per capita have the most diversified sources, with the higher incomes from casual, salaried, and business labor income, although income from livestock still accounts for the largest share. Households with more than 4.5 TLU per capita, in contrast, rely primarily on livestock husbandry with very little focus on non-livestock activities. This observation suggests that, to a large extent, the diversification of income sources among livestock-poor households is primarily a coping mechanism in response to declining herd size. In addition, as expected, the poorest households rely more on transfers and food aid than the asset rich. The few households (4.16%) that do have an aggregated salary income of at least 10,000 Ksh per month irrespective of livestock owned depend little on livestock, with salary contribution accounting for about 74.1% of income. This is indicative of gradual exit from a livestock to a non-livestock based lifestyle among such households. As expected, livestock-poor households rely more on cash transfers and food aid than households with more livestock.

Table 9 Percentage contribution of incomes by asset category (TLU per capita)

Income source	<=1 TLU	>1 TLU<=2	>2 TLU<=4.5	>4.5 TLU per capita	With a monthly salary >Ksh 10,000 irrespective of herd size
Livestock	48.8	78.8	86.3	93.5	18.1
Casual labor	12.3	3.1	2.3	1	0.2
Salary income	3.3	2.7	1.7	0.9	74.1
Business	17.6	6.2	3.6	2.2	5.7
Crop income	3.5	1.5	0.6	0.1	0.6
Net transfers	3	2	1.4	0.7	0.3
Cash aid	6.2	3.1	1.9	1	0.5
Food aid	4.4	2.1	2	0.6	0.3

Note: The statistics are based on data for the 924 households in each year.

1.5.3 Income and Asset poverty classifications

Income and asset poverty decompositions derived using both the asset index and TLU per capita are shown in Table 10 (with corresponding scatter plots in appendix 2 and 3). The results based on the asset index (panel A) indicate that between 2009 and 2013, the majority of households remain structurally poor. Overall, the number of stochastically poor increases marginally during the period while that of the structurally poor, who are in the majority, is highest in 2010 (63.9%) and then declines to 47.7% in 2013. It is also worth noting that the number of the structurally nonpoor remains quite stable, varying from 14.7 % in 2009 to 16.8 % in 2013, although there is a notable reduction in 2010 and 2012, which could be attributed to a reduction in the returns to productive assets during each of the previous years (2009 and 2011 respectively) which were drought periods.

Table 10 Structural and stochastic poverty decomposition based on the asset index

	2009	2010	2011	2012	2013
Panel A: Asset index poverty					
Stochastically poor	26.5	15.9	28.5	22.3	23.5
Structurally poor	46.2	63.9	43.4	53.2	47.7
Stochastically nonpoor	12.6	12.1	14.0	12.1	12.1
Structurally nonpoor	14.7	8.1	14.1	12.5	16.8
Panel B: TLU poverty					
Stochastically poor	5.8	9.7	3.7	3.8	1.7
Structurally poor	66.8	70.1	67.9	71.8	69.3
Stochastically nonpoor	13.1	7.8	17.8	18.2	19.4
Structurally nonpoor	14.3	12.3	10.7	6.3	9.6

Note: The statistics are based on data for the 924 households in each year.

The poverty decomposition based on TLU is reported in Table 10 panel B. The majority of households are structurally poor, rising from 66.8% in 2009 to 69.3% in 2013 primarily through de-accumulation of assets. Those that escape poverty do so stochastically, from 13.1% in 2009 to 19.4% in 2013. The number of stochastically poor decreases from 5.8% in 2009 to 1.7% in 2013, possibly because of diminishing livestock assets that push households to structural poverty. The TLU measure shows a decrease in the structurally nonpoor, from 14.3% in 2009 to 9.6% in 2013. These results resemble those of Radeny et al. (2012) and Carter and May (2001), who report high structural poverty, limited upward structural mobility, and increasing upward stochastic mobility among sampled households in Kenya and South Africa, respectively.

According to both the asset index and TLU per capita, between 2009 and 2013, the majority of households remain structurally poor. There are, however, notable differences: First, the TLU approach identifies higher proportions of structurally poor and stochastically nonpoor than does the asset index. Second, only the TLU approach points to a consistent decrease in the number of structurally nonpoor. Third, the TLU approach shows a decrease in stochastically poor households, whereas the asset index identifies an increase.

Given the pastoralists' reliance on livestock and the nature of the nonmarket pastoral economy with its limited non-livestock assets, we tend to prefer the results from TLU per capita.[11] In a pastoralist setting, the value of the asset index is driven not only by the livestock owned, but also by prevailing prices. For example, during the 2011 drought, we observe a decline in TLUs but an increase in livestock value, which is driven by price increases that stem primarily from the losses incurred by the pastoralists, which for all practical purposes constitute a loss in assets. Moreover, because pastoralists generally use their produce and livestock for subsistence and risk management rather than trading, price increases do not necessarily translate into increased wealth.

Finally, to assess the effect of food aid on the poor, we estimate the poverty decompositions with the food aid variable excluded but find minimal differences in poverty dynamics among the households. Only a few (less than 5%) fall into structural poverty across the survey period, implying that food aid, although critical in helping households cope with short term hunger problems, is not effective in long-term poverty alleviation.

[11] To compare the predictive accuracy of the asset index and TLU per capita, we use Theil's U-statistic, defined as $U_i = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2\right]^{1/2}}{\left[\frac{1}{n}\sum_{i=1}^{n}A_i^2\right]^{1/2} + \left[\frac{1}{n}\sum_{i=1}^{n}P_i^2\right]^{1/2}}$, where A_i is the actual value and P_i is the predicted value from the model. This statistic measures how past asset index or TLU per capita (*t*-n) predicts the current asset index or TLU poverty (*t*) for household (*i*). Theil's U-statistic uses a forecasting model to predict the accuracy of a given indicator measured on a range from 0 to 1, with lower values reflecting a more accurate prediction (Theil 1966). We obtain U-values of 0.29 and 0.54 for the asset index and TLU per capita, respectively, which indicates that the asset index is a better predictor of future (asset index) poverty than TLU per capita. Nevertheless, one must take into account that Theil's U statistic for the asset index is based on imputed values, whereas the corresponding value in the TLU case is based on actual values. As imputed values tend to have a lower variation, it comes as no surprise that Theil's U statistic for such measures are larger than those based on actual observations.

1.6 Conclusions

In this study, we use five waves of household panel data to empirically analyze income and asset-based poverty. In particular, we demonstrate that livestock remains the main source of livelihood among pastoralists, with livestock income accounting for over 70% of total household income. We also observe a gradual diversification of livelihood into other non-livestock income activities, mainly among households with few livestock. Households with more livestock, in contrast, continue to focus mainly on livestock husbandry. As a result, livestock income accounts for about 94% of income for households with more than 4.5 TLU per capita but under 50% for households with one or less TLU per capita. As herd sizes decline, households have a greater demand for income from alternative sources and thus turn increasingly to non-livestock activities to help smooth their consumption and meet other immediate household needs.

Poverty levels in both income and assets are high: in 2013, approximately 73% of households were income-poor, and 88% were livestock-poor (i.e., less than 4.5 TLU per capita). The decomposition of structural and stochastic poverty also implies that over the study period, the majority of households sampled remain structurally poor, with incomes and assets falling below their respective poverty lines, while the stochastically nonpoor only increase marginally. Conversely, the number of structurally nonpoor households is small across all survey waves.

Methodologically, this study compares estimates of asset poverty using both an asset index and TLU per capita. As the asset index is derived from predictions of expected income based on the stock of productive assets while the TLU approach assumes a fixed threshold of livestock owned at a given time, they produce notably different poverty assessments. There is an implicit assumption in computing the asset index that households respond to price changes by selling more livestock and livestock products when prices are high, which results in higher incomes. In reality, this study shows that such may not be the case among pastoralists, who rarely sell animals and milk even at favorable prices. Such reluctance to sell may stem not only from the livestock's important economic value but also from their social insurance function, which facilitates important social networks that are especially helpful in times of need. Furthermore, access to markets is often limited. The influence of commodity prices on the asset index also means that the volatility of these prices influences the volatility of asset-index measure. A good illustration in our analysis is asset poverty during the 2010-2011 drought period, which shows a nearly 20 percentage point *decline* when measured with the asset index, but a seven percentage point *increase* when assessed using the TLU approach. This large – and highly counterintuitive – drop in poverty is mostly the result of the approximately 60% increase in milk prices in 2011. Thus, in a nomadic setting in which the use of productive assets (beyond livestock) is limited and production is aimed primarily at home consumption, the asset-index approach can give rise to misleading results, which makes the TLU-based asset poverty approach conceptually more convincing. The (more commonly applied) asset-index approach, which is largely derived from income, is more suited to a broader wealth and income portfolio. As such, this paper highlights the importance of context in the application of appropriate metrics to understand household wealth and its dynamics.

Overall, the analysis provides clear empirical evidence that poverty is widespread among pastoralist households in the study area. Although the local economy seems to be slowly shifting away from pure pastoralism to include increasing opportunities for non-livestock income generation, pastoralism will continue to be the most productive livelihood option for a majority of households. Thus, policies such as livestock insurance (that can help to reduce the impact of shocks on pastoralist households), as well as improved livestock input markets (that can deliver water, feeds, and veterinary inputs) are particularly important.

For livestock poor households, policies that promote livelihood diversification would be appropriate within a package that targets poverty graduation and livelihood enhancement. Similarly, multiple programs such as cash or asset transfers, provision of affordable loans, and training in business development skills will enable households to engage in economic activities that raise their incomes and build their productive assets. Poverty graduation programs are for this reason increasingly and successfully deployed for purposes of promoting resilience and improving livelihoods for the extreme poor (Banerjee et al., 2015).

Chapter Two: Livestock asset dynamics among pastoralists in Northern Kenya

Abstract

Understanding household-level asset dynamics has important implications for designing relevant poverty reduction policies. To advance this understanding, we develop a microeconomic model to analyze the impact of a shock (e.g., a drought) on the behavioral decisions of pastoralists in Northern Kenya. Using household panel data this study then explores the livestock asset dynamics using both non-parametric and semi-parametric techniques to establish the shape of the asset accumulation path and to determine whether multiple equilibria exist. More specifically, using tropical livestock units as a measure of livestock accumulation over time, we show not only that these assets converge to a single equilibrium but that forage availability and herd diversity play a major role in such accumulation.

Key words: Poverty dynamics, pastoralists, assets, semi-parametric estimation, Kenya

2.0 Introduction

Even though globally the number of people living in extreme poverty declined from 1.9 billion in 1990 to 836 million in 2015, poverty alleviation remains a key challenge for many countries across the world. In sub-Saharan Africa, for example, over 40% of the population still lives in extreme poverty (i.e., less than $1.25 per day), which the United Nations hopes to eradicate by 2030 as one of its sustainable development goals (United Nations 2015). Another goal is to halve the proportion of those living in poverty in all its dimensions[12] over the same period (OECD 2013; United Nations 2015). Achieving these aims, however, is dependent on effective policies, whose design requires a clear understanding of the underlying welfare dynamics that determine how households escape from or fall into poverty. One particularly crucial factor for poverty alleviation

[1] Poverty dimensions encompass a range of deprivation factors, including poor health, lack of income and education, inadequate living standards, poor work quality, and threat of violence (OECD 2013).

is household accumulation of assets, particularly productive assets that enable them to raise their incomes.

Among pastoralists living in arid and semi-arid areas the key asset for income, food security, wealth, and social status is livestock (Swift 1986), which researchers therefore use as the primary measure to assess poverty and wealth dynamics within this population. In Kenya for example, the pastoralist flock accounts for 50–70% of Kenya's total livestock production (Idris 2011). Despite this considerable contribution, pastoralist livestock are a relatively risky asset, with changes in herd sizes greatly affected by drought and illnesses (Fafchamps 1998). Pastoralist areas in Northern Kenya are particularly characterized by chronic vulnerability to drought-related shocks which has been leading to declining herd sizes over time (Chantarat et al. 2012). The area has experienced 28 droughts in the past 100 years, 4 of the largest in the period 1998-2008 (Adow 2008).

This study throws further light on the effect of drought on livestock asset dynamics through a three-stage exploration among pastoral households in Northern Kenya's Marsabit district. First, we develop a microeconomic model with which to analyze the impact of a shock like drought on the pastoralists' behavioral decisions. Second, using tropical livestock units, we apply both nonparametric and semiparametric methods to identify the shape of asset accumulation path and determine the presence (absence) of single and multiple dynamic equilibria. By doing so, we are able to verify the existence of poverty traps. Third, because livestock is this population's main source of livelihood, we assess how household characteristics and environmental factors influence livestock accumulation over time, an aspect that warrants closer examination given the prevalence of droughts and inadequate insurance mechanisms.

This study contributes to the literature in four ways: First, few of the extant empirical studies on asset dynamics in developing countries provide a theoretical model that can explain how households react to environmental change. To begin filling this gap, our microeconomic model sheds light on how a shock influences such factors as livestock holdings, consumption, and aid. Second, because our work draws on unique panel data from the International Livestock Research Institute's (ILRI) Index-Based Livestock Insurance (IBLI) project, it is one of the most comprehensive studies to date on asset dynamics among pastoralists. Third, our analysis extends previous research by applying both non- and semiparametric techniques to compare the estimations of livestock asset dynamics. Finally, our investigation identifies the effect of forage availability (proxied by satellite data) on livestock accumulation, which few other studies do.

2.1 Asset dynamics model

Household welfare dynamics tend to be described in terms of three presumptions: unconditional convergence, conditional convergence, or multiple dynamic equilibria (Carter and Barrett 2006). Unconditional convergence hypothesizes that all households tend to move to a single long-term equilibrium, meaning that asset dynamics follow a concave path. Under conditional convergence, welfare dynamics follow a similar path to that in single stable equilibrium except that each household subgroup moves toward its own equilibrium. In both the conditional and unconditional convergence conditions, therefore, poverty traps can only occur if the long-term equilibrium is below the poverty line. Under the multiple dynamic equilibria presumption, however, the welfare path follows a nonconvex pattern with two stable high and low equilibria and an unstable threshold point (Naschold 2013). Households with assets below the unstable threshold point lose their assets and tend toward a chronically poor state, while households with assets above the threshold point tend to accumulate assets and move toward higher levels of welfare.

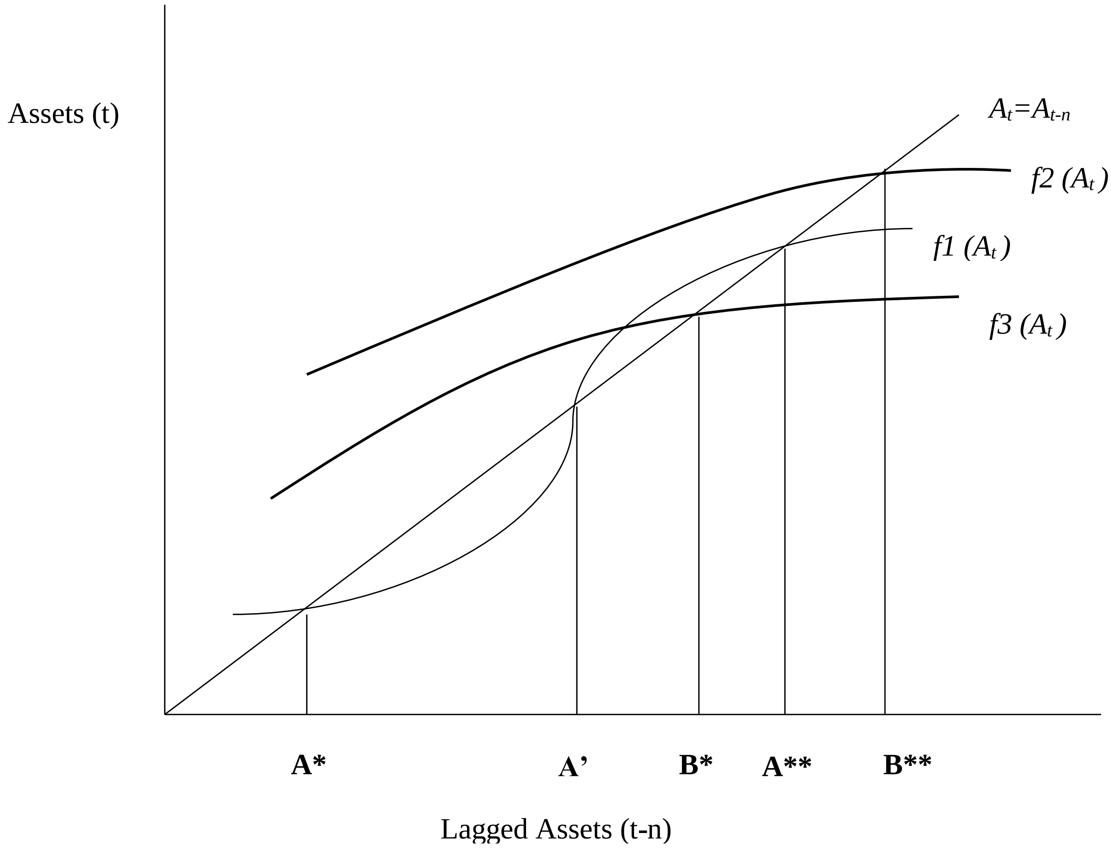

Figure 3 Different asset accumulation paths

In the different paths depicted in Figure 3, the vertical axis shows the current assets (A_t) and the horizontal axis, the lagged asset holdings (A_{t-n}). Unconditional convergence is represented by line f_2 (A_t) for which only a single equilibrium exists at its intersection with the 45^0 line. Conditional convergence is represented by functions f_2 (A_t) and f_3 (A_t) for different household subgroups, each with its own equilibrium. The unconditional convergence represented by functions f_2 (A_t) and f_3 (A_t) implies structural asset poverty if the stable equilibrium points **B*** and **B**** lie below the poverty line. Line f_1 (A_t), which crosses the 45^0 line three times, represents multiple dynamic equilibria, with points **A*** and **A**** designating a stable low-level and high-level equilibrium, respectively, and Point **A'** representing the unstable threshold point at which assets bifurcate. When the poverty line lies below A**, point A' represents the dynamic asset poverty threshold moving above which leads to asset accumulation until long-run equilibrium is reached at point A**. Movement below A' propels households toward the low-level equilibrium at A*.

Clearly identifying the levels and shape of household welfare dynamics has important policy implications. For a single dynamic equilibrium, the key question is whether the equilibrium is below or above the poverty line. If above the poverty line, then policy needs to focus on how to support households in maintaining and raising their welfare levels so as to speed up the convergence process. If the equilibrium is below the poverty line, households are likely to be trapped in poverty, implying a need for structural changes that raise household welfare levels. In the case of pastoralists, this latter could take the form of more livestock provision accompanied by such asset protection measures as livestock insurance and forage preservation. In the presence of multiple equilibria, it is the household's initial condition that matters. If the household starts above (below) the critical threshold, it can be expected to move toward higher (lower) welfare levels. This situation thus requires policy measures that ensure households do not fall below the threshold, especially after adverse shocks. In this case, designing efficient policies requires clear identification of the threshold point (Naschold 2012; Giesbert and Schindler 2012).

To assess how shocks that shift pastoralists away from such an equilibrium translate into behavioral changes, we develop a model based on standard neoclassical growth (Romer 1994; Mixon and Sockwell 2007; Walsh 2000). We focus on a representative pastoralist agent characterized by the following utility function:

$$u\left(c_t, l_t^h, l_t^e\right) = c_t^\alpha + \beta ln\left(1 - l_t^h\right) + \gamma ln(1 - l_t^e) \qquad (1)$$

where c_t is consumption in period *t*, l_t^h is labor time allocated to one's own livestock in period *t*, and l_t^e is labor time on the local labor market, where $\alpha \in (0,1]$ and $\beta, \gamma \in \mathbb{R}_+$. The pastoralist agent must thus choose between l_t^h and l_t^e while taking the following time constraint into consideration:

$$l_t^h + l_t^e + F_t = \omega_t \qquad (2)$$

where $F_t = \mathrm{F}$ is leisure time, and $\omega_t = \omega$ is total available time. Normalizing $\omega - F = 1$ then yields the following constraint:

$$l_t^h + l_t^e = 1 \tag{3}$$

Because our setting is intertemporal, the pastoralist agent faces the following optimization problem (with $\xi \in (0,1]$ being the pastoralist's intertemporal discount factor and E_0 the expectations operator):

$$max_{c_t, l_t^h, l_t^e, k_{t+1}} E_0\left[\sum_{t=0}^{\infty} \xi^t u\left(c_t, l_t^h, l_t^e\right)\right] \tag{4}$$

This latter is subject to the following constraints:

$$k_{t+1} = k_t{}^{\tau} - \delta k_t{}^{\tau} + l_t^h k_t{}^{\tau} - c_t + w_t l_t^e + (\mu) * ex\,p(z_t) * k_t^{\tau} + A(k_t, z_t) \tag{5a}$$

$$l_t^h + l_t^e = 1 \tag{5b}$$

$$\lim_{t \to \infty} \xi \frac{u'(c_{t+1})}{u'(c_0)} k_t = 0 \tag{5c}$$

$$z_t = \rho z_{t-1} + \varepsilon \qquad \epsilon \sim N(0, \sigma^2) \tag{5d}$$

Equation (5a) describes the transition equation of capital (i.e., the motion of livestock over time, with $\tau \in (0,1)$ being the elasticity of livestock accumulation). Capital in k_{t+1} is thus influenced by the time-independent depreciation rate δ (where $\delta \in (0,1)$), the pastoralist consumption c_t in *t*, and the share of time devoted to l_t^h and l_t^e. This last aspect, time allocation, is the crucial decision for pastoralists in rural areas who can either tend their own livestock or work for a certain wage w_t in the labor market. Capital stock can also be influenced by the shock term $(\mu) * exp(z_t)$, where z_t is assumed to be an *AR(1)* autoregressive shock process (where $\rho \in (0,1)$), and μ (where $\mu \in \mathbb{R}_+$) reflects the impact of the shock on the pastoralists' livestock. We further assume that the pastoralists receive aid, represented by the function A: $\mathbb{R}^2 \longrightarrow \mathbb{R}_+$, where $A(k_t, z_t) > 0, \frac{\partial A(k_t,z_t)}{\partial k_t} < 0 \ \nabla\, k_t \in \mathbb{R}\backslash\{0\}$ and $\frac{\partial A(k_t,z_t)}{\partial z_t} < 0 \ \nabla\, z_t \in \mathbb{R}$. The second constraint is given by the time constraint from Equation (5b), the third constraint (Equation 5c) is the so-called transversality condition, which ensures that ultimately, no capital is left. Because the marginal benefit of working in the labor market is determined by wage w_t, our model also includes the optimization problem for a representative firm:

$$max_{l_t^e} Q(l_t^e) = y(l_t^e) - \varphi(l_t^e) \tag{6}$$

with y and φ given by:

$$y(l_t^e) = P(l_t^e)^{\Gamma} exp(z_t)$$

$$\varphi(l_t^e) = w_t l_t^e$$

For the sake of simplicity, we assume that firms only use labor l_t^e as an input factor in the production function y, where $(P \in \mathbb{R}_{+})$ is the total factor productivity and Γ $(\Gamma \in (0,1))$ is the output elasticity. We also normalize prices to 1. Again, $exp(z_t)$ represents the impact of the *AR (1)* shock process on the firm's output, while $\varphi(l_t^e)$ reflects the explicit cost function. The representative firm maximizes its profit $Q(l_t^e)$ by choosing the optimal amount of labor l_t^e in each period *t*.

If we solve both optimization problems (Equations (4) and (6)), we can reformulate the resulting calculations to obtain equations (7a), (7b) and (7c) and combine with equations (5a), (5b) and (5d) as the following set of characterizing equations for the model:

$$\xi E_t\{c_{t+1}^{(\alpha-1)}[(l_{t+1}^h + 1 - \delta + (\mu)exp(z_{t+1}))\tau {k_{t+1}}^{\tau-1} + \frac{\partial A(k_{t+1}, z_{t+1})}{\partial k_{t+1}}]\} = c_t^{(\alpha-1)} \tag{7a}$$

$$\frac{(1-l_t^h)}{(1-l_t^e)}\frac{\gamma}{\beta} = \frac{w_t}{{k_t}^{\tau}} \tag{7b}$$

$$w_t = P\Gamma {l_t^e}^{(\Gamma-1)} exp(z_t) \tag{7c}$$

$$k_{t+1} = {k_t}^{\tau} - \delta {k_t}^{\tau} + l_t^h {k_t}^{\tau} - c_t + w_t l_t^e + (\mu) * exp(z_t) * k_t^{\tau} + A(k_t, z_t)$$

$$l_t^h + l_t^e = 1$$

$$z_t = \rho z_{t-1} + \varepsilon$$

Equation (7a) can be interpreted as the Euler equation that links consumption in period *t* to consumption period *t+1.* It is evident that the intertemporal consumption decision depends not only on the expected work time allocation in the next period but also on expectations of the marginal benefits of next period's aid. We also observe that the proportion of l_t^h and l_t^e is related to both capital stock and wage (equation 7b) and that wage is positively influenced by the pastoralist's external labor force participation (equation7c). Given our interest in how a shock affects equilibrium, we must first solve for a steady state. Because we cannot solve for a steady state algebraically without restricting our model, we compute the steady state results numerically.[13]

The analysis also requires that we specify an explicit form for our aid function A:

$$A(k_t, z_t) = \frac{\theta}{exp(k_{t)}} + r - \zeta exp(z_t), \tag{8}$$

This specification satisfies the conditions for the aid function outlined above; that is, it is characterized by a constant stream of aid, $r \in \mathbb{R}_+$, and two parameters $\theta \in \mathbb{R}_+$ and $\zeta \in (0,1]$, which represent an aid sensitivity factor with regard to livestock and the extent of the aid flow's reaction to shock, respectively. The aid stream thus depends inversely on the pastoralists' capital stock, as well as on the impact of particular shocks. Based on previous literature and economic considerations (Wang et al. 2016; Liebenehm and Waibel 2014; Poulos and Whittington 2000; Holden et al. 1998 for time preferences), we use the parameter values in Table 11 to compute the steady state:[14]

Table 11 Parameter values used to compute the steady state

α	β	γ	ξ	ζ	μ	δ	θ	r	P	τ	ρ	σ	Γ
0.5	*1*	*2*	*0.8*	*0.5*	*1*	*0.05*	*3*	*2*	*1*	*0.78*	*0.92*	*0.1*	*0.8*

[2] For both the steady state computation and the analysis, we use the Dynare software package implemented in Matlab. Because Dynare solves for steady state using a nonlinear Newtonian solver that does not work in all specifications, in these latter cases, we derive valid results by applying the homotopy concept (For more information see (Whitehead 1978)).

[3] Because we assume that the disutility of working in the external labor market is higher for pastoralists than tending their own livestock, we set $\gamma > \beta$. We also use the regional sensitivity analysis implemented in Dynare to check for parameter values which can cause no stable solutions of the system (Ratto, 2009). By using the Kolmogorov-Smirnov test statistic we identify only ξ, μ and τ as being potential driver for instability. In particular, low values of ξ will lead to a non-convergence of the model.

These parameters yield one single stable equilibrium characterized by the following steady state values in Table 12 as follows:

Table 12 Estimated steady state values

Variable	$\bar{c}$	$\bar{l}^e$	$\bar{l}^h$	$\bar{k}$	$\bar{z}$	$\bar{w}$	$\bar{A}$
Steady state value	*10.1521*	*0.077694*	*0.922306*	*14.1868*	*0*	*1.33356*	*1.5*

In equilibrium, we obtain a relatively high value for consumption relative to that for livestock (approximately 71% of the livestock score), which might be expected to give our assumption of a high discount rate (and thus a low discount factor). In our model, the low discount factor forces our representative agent (the pastoralist) to consume his livestock in the current period instead of saving it to produce more livestock tomorrow, which is in line with the empirical findings by (Liebenehm and Waibel 2014; Holden et al. 2000). The allocation of time to internal and external labor forces also shows a plausible pattern: our pastoralist devotes about 92% of his time to his own livestock and only about 8% to working elsewhere in the local economy. Figure 4 illustrates the k_t policy function, which maps the livestock of period *t-1* onto the livestock in period *t* while all other variables remain unchanged (i.e., it is a function of the form $k_t = g(k_{-1})$). As expected in second order Taylor polynomial approximation, the policy function *k* is concave and intercepts with the 45° line at about 14.1. This outcome indicates that the pastoralist accumulates livestock until a value of about 14.1, which is the stable equilibrium. If a positive or negative shock occurs, the livestock returns to its initial value. The function's special concave pattern, which includes a diminishing slope,[15] is a result of our using a second-order Taylor polynomial approximation in calculating the steady state.

[4] Using a first-order approximation does not affect the steady state value, but the policy function is linear rather than concave.

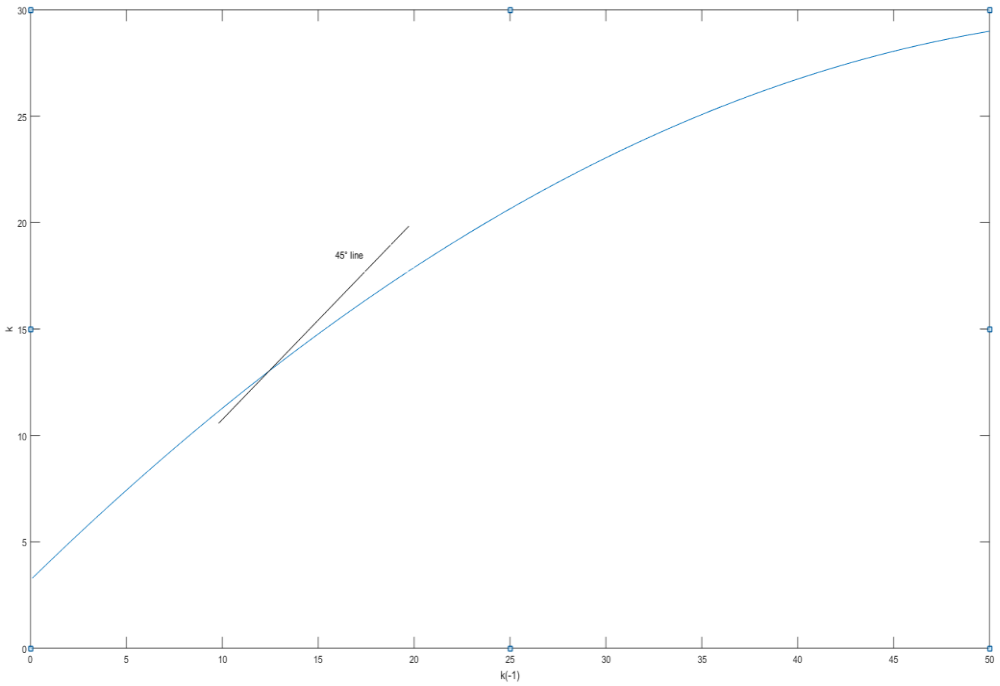

Figure 4 Policy function for k_t

Of particular interest to our analysis is the effect of a shock on the transition back to the steady state. To shed light on this issue, we use the impulse response function graphs displayed in Figure 5. In this analysis, we consider a negative one standard deviation shock to the system, with all variables set to their steady state values in the initial situation (and a normalized steady state value of 0 for all variables). The shock influences the economy in several ways. First, it forces a one standard deviation decrease in the *AR(1)* process in the first period with a smooth and monotonic increase back to the steady state value thereafter. Because the shock term is also included in the aid function, aid immediately has a positive reaction to the negative shock. However, the aid function is also influenced by a second factor: the shock's negative influence on the pastoralist's livestock, which is reflected in the graph by the decrease in capital stock k_t in the first period. Because aid is assumed to be negatively related to the pastoralist's livestock, this influence again leads to a reinforcement of aid's positive reaction. The shock also engenders a decrease in wages, which in turn has an immediate feedback effect on the pastoralist´s decision on time allocation for labor and thus on capital accumulation. The fact that our livestock accumulation function is concave in k produces higher marginal returns with a lower capital stock, which results in the pastoralist allotting more time to tending his own livestock. This effect is again reinforced by the negative wage effect in the labor market, which decreases his incentives to seek work in the local economy.

As regards consumption, the pastoralist reduces consumption slightly up to a certain point but then increases it again until it reaches the old equilibrium. In fact, comparing the different shock reactions of capital and consumption shows no sudden reduction in consumption during the first period but rather a smooth (and thus delayed) adjustment that leads to a reinforcement of capital stock reduction in the following period and consequently, a reduction in consumption. This process continues until the capital stock starts to grow again (due to the reinforcement of the pastoralist tending his own livestock), which also drives an increase in consumption. As regards the time needed for the economy to adjust, it takes about 60 periods for consumption, capital, aid, the *AR(1)* process, and the wage to return to equilibrium. Both labor time allocations (l_t^e, l_t^h) reach their initial steady state values after about 5–8 periods, which is the same point in time that capital and consumption are at their lowest levels. During this period, the pastoralist increases the time spent working in the local economy while decreasing the time taken tending his own livestock relative to the steady state value. After this short increase (decrease) in labour, the work time decisions converge (with slight fluctuations) back to the steady state, reaching initial values after about 40 periods.

In sum, a negative shock like a drought leads to an immediate decrease in livestock followed by a smooth reduction in consumption. Because the shock also affects the local economy, it prompts a wage decrease, which reinforces the pastoralist's incentives to tend his own livestock and reduce time spent in the external labor market. Whereas the pastoralist's labor time allocation shows a pattern of quick convergence, however, the adjustment of other variables takes much longer. Finally, although aid initially increases in response to the shock, thereafter it converges smoothly.

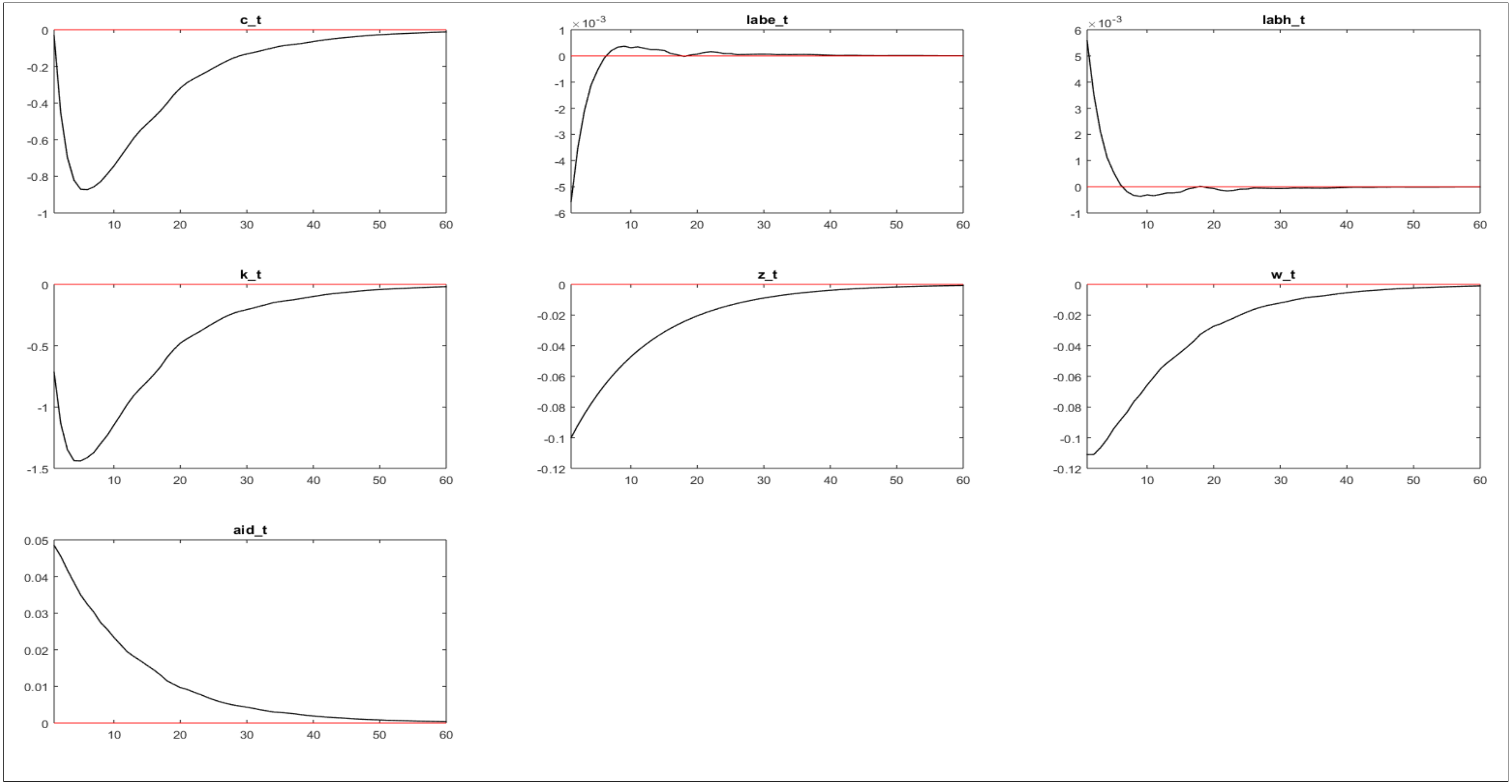

Figure 5 Impulse response functions of a one standard deviation shock

Note: The horizontal axes are time periods. The vertical axes can be interpreted as deviations from the generalized steady state (for more information, see (Pfeifer 2014) *Source:* Authors' own calculations using Dynare.

In addition to assessing immediate reactions to a shock, we also examine how the local pastoralist economy develops over time. To do so, we simulate the economy based on our randomized shock distribution and compute the time paths for the variables of interest. We run our simulations twice: once assuming a comparatively low volatility for shocks ($\sigma = 0.1$) and again assuming a comparatively high volatility ($\sigma = 0.2$). Figure 6, which illustrates the different time patterns for internal and external labor, capital, and consumption for different values of σ, reveals several interesting insights. First, the lower bound of the fluctuations in capital and consumption reveals no large differences in the fluctuation patterns of low versus high volatility cases, implying that shock volatility plays no crucial role in determining the (absolute) negative impact on a pastoralist's livestock. This observation suggests that low shock volatility does not necessarily lead to an increase in periods with very low capital stocks. This finding does not hold, however, for the upper bound in which higher volatility leads to more and longer periods of higher capital accumulation (and higher consumption).

The graphs for internal and external labor follow the same pattern, with the lower bound (external labor) and higher bound (internal labor) of the two fluctuation patterns showing little difference. The upper bound (external labor) and lower bound (internal labor), however, reveal stronger differences in the labor time allocation in the high volatility case, which can also be linked to the pattern of consumption and capital. Comparing the two upper and two lower graphs reveals that the pastoralist tends to increase his external labor force only in periods during which the economic cycle reaches its peak, implying that when volatility is low, he focuses mainly on tending his own livestock.

Overall, these findings suggest that when shock volatility is comparatively low, pastoralists focus on tending their own livestock, but simulating an economy with high volatility produces higher positive fluctuations in both capital and consumption. In periods with high capital stock, these fluctuations tend to move pastoralists away from tending their own livestock (internal labor) toward working in the local labor market (external labor). The underlying rationale is that in boom phases of the economy, both livestock and wages are quite high, so the marginal utility of external labor (wages) is higher and more beneficial to the pastoralist, than the marginal utility of internal labor.

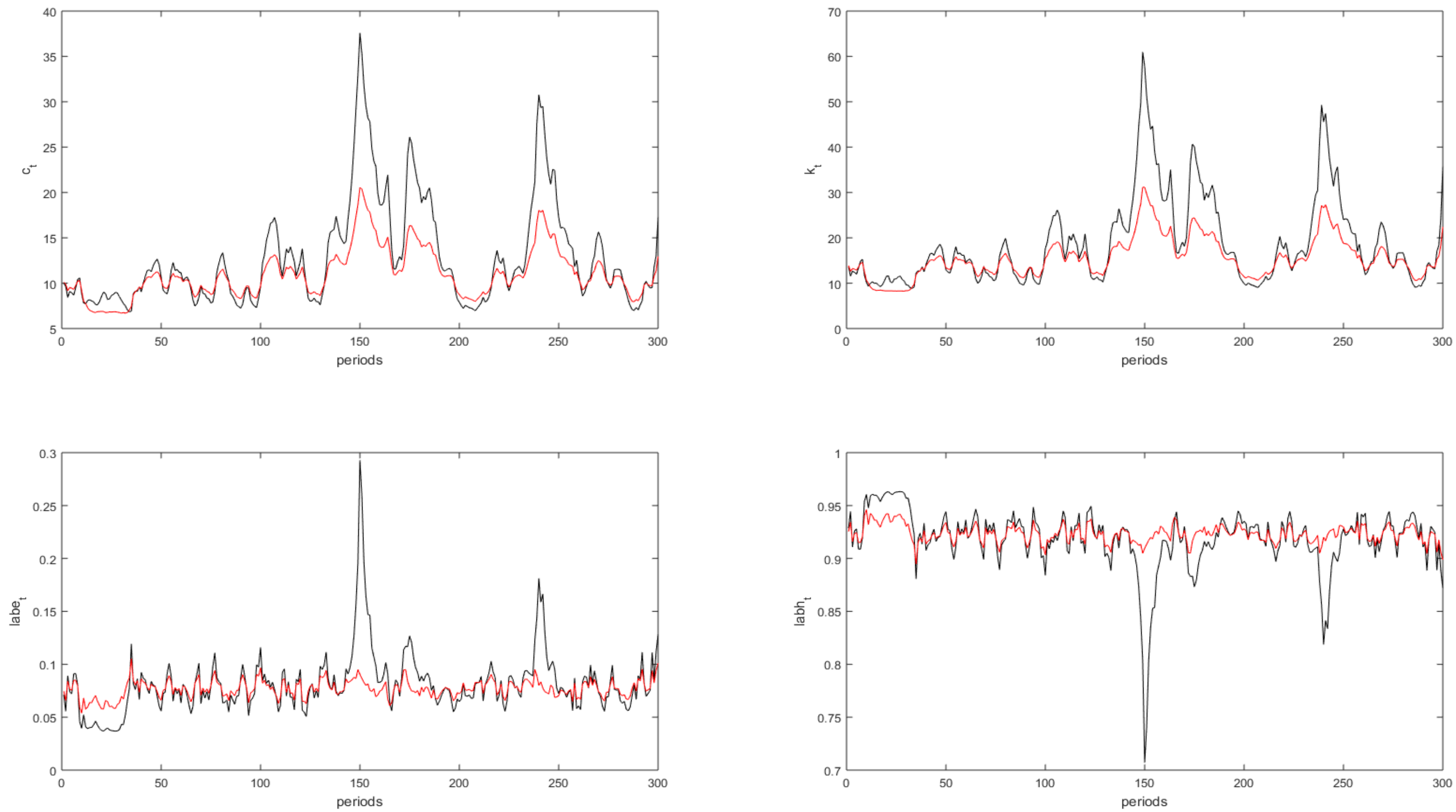

Figure 6 Simulations of the economy with low ($\sigma = 0.1$, red line) and high volatility ($\sigma = 0.2$, black line)

Source: Authors' own calculations using Dynare.

2.2 Previous Literature

Although several studies have investigated household welfare dynamics, their conclusions differ: some point to only a single equilibrium, while others identify multiple equilibria. For example, in a longitudinal exploration of asset accumulation determinants in Bangladesh aimed at explaining why some households are trapped in poverty, Agnes and Baulch (2013) identify a single low-level equilibrium with no evidence for multiple equilibria. Likewise, Naschold (2012), in a study of poverty dynamics in rural semi-arid India, finds only a single stable equilibrium ranging between 2.8 poverty line units (PLUs) for a one-year lag and 3.2 PLUs for a three-year lag. A similar convergence to a single equilibrium close to the poverty line (about 9.95 PLUs or approximately US147 dollars annual income per adult) is also reported by Giesbert and Schindler (2012) in their exploration of welfare dynamics among rural households in Mozambique. On the other hand, Barrett et al.'s (2006) analysis of panel data from five different sites in rural Kenya and Madagascar identifies multiple dynamic equilibria. Specifically, herd dynamics bifurcate at 5-6 TLU per capita, above which level herd size grows to a higher equilibrium of 10 TLU per capita and below which it tends to decline to a low-level equilibrium of less than 1 TLU per capita. A similar analysis by Lybbert et al. (2004) using 17 years of herd history data (1980–1997) from four communities in Southern Ethiopia’s Borana plateau also reveals two stable lower and higher asset equilibria at herd sizes of one and 40–75 animals, respectively. The threshold point for the unstable equilibrium is at around 10–15 animals. Such multiple equilibria are not identified, however, in Mogues’ (2004) nonparametric analysis of livestock asset dynamics in Ethiopia, which shows only a convergence to 3.5 TLUs over a three-year period. Nevertheless, Liverpool-Tasie and Winter-Nelson's (2011) estimation of asset and expenditure-based poverty using 1994–2004 panel data for Ethiopia reveals both a low and high stable equilibrium, although it is worth noting that these authors used an asset index based on a range of household assets.

The research also indicates that social, economic, and environmental shocks are important determinants of household poverty. For example, Agnes and Baulch (2013) show that negative shocks have negative effects on asset accumulation, while positive shocks such as remittances and dowry lead to asset accumulation. For pastoralists specifically, Lybbert et al. (2004) establish that both household characteristics (such as income) and covariate risks (most notably drought) play a major role in wealth dynamics. Indeed, the serious effects of drought and hurricanes on poor households in Ethiopia and Honduras are clearly illustrated by Carter et al. (2007), who demonstrate that during times of food shortage, these households destabilize their consumption and preserve the few assets they own for future survival. The families even reduce the number of meals per day or serve smaller food rations. Zimmerman and Carter (2003) further show that because poor households have less profitable assets, when faced with income shocks, they pursue asset smoothing rather than consumption smoothing. This observation is confirmed by Hoddinott (2006), who finds that poor households faced with income losses smooth their assets, while non-poor households sell livestock to smooth consumption.

The extant research also underscores the major role of social networks in building household resilience. For example, several studies show that social capital is key in mitigating the risks faced by households and thus helping them recover after loss (Fafchamps 2000; Fafchamps and Minten 1999; Mogues 2004; Liverpool-Tasie and Winter-Nelson 2011). Both household social ties and the nature of relationships affect the levels of asset holding over time. For instance, in the pastoral setting, informal sharing of livestock allows households to borrow livestock after loss as an informal insurance arrangement. Conversely, persistently poor households are systematically excluded from social networks that could provide credit that would enable them to respond to shocks (Lybbert et al. 2004; Santos Barrett 2011). Hence, in an environment in which formal insurance and credit markets are unavailable, social groups and networks serve an important role in risk management and the provision of cheap credit. Studies also show that gender-based associations and kinship groups allow farmers to overcome periods of climatic and economic difficulties (Goheen 1996).

2.3. Study Area and Data

2.3.1. Study area

Our study area, Marsabit district, is characterized by an arid or semi-arid climate (rainfall of up to 200 mm/year in the lowlands and 800mm/year in the highlands), drought, poor infrastructure, remote settlements, low market access, and low population density (about 4 inhabitants per km^2). This area, which covers about 12% of the national territory, is home to about 0.75% of the Kenyan population and encompasses several ethnicities – including Samburu, Rendille, Boran, Gabra, and Somali – each with its own distinct language, culture, and customs. These pastoral communities live in semi-nomadic settlements in which livestock, the main source of livelihood, is moved across vast distances in search of grazing pastures, especially during the dry season. Largely dependent on milk from livestock (mainly camels or cattle) for home consumption, these communities also trade or sell animals (primarily goats and sheep) to purchase food and other commodities (Fratkin et al. 2005). Marsabit has two major ecological/livelihood zones: an arid and primarily pastoral upper zone and a semi-arid, more agro-pastoral lower zone. Figure 7 shows the distribution across the district of the 16 sublocations under study.

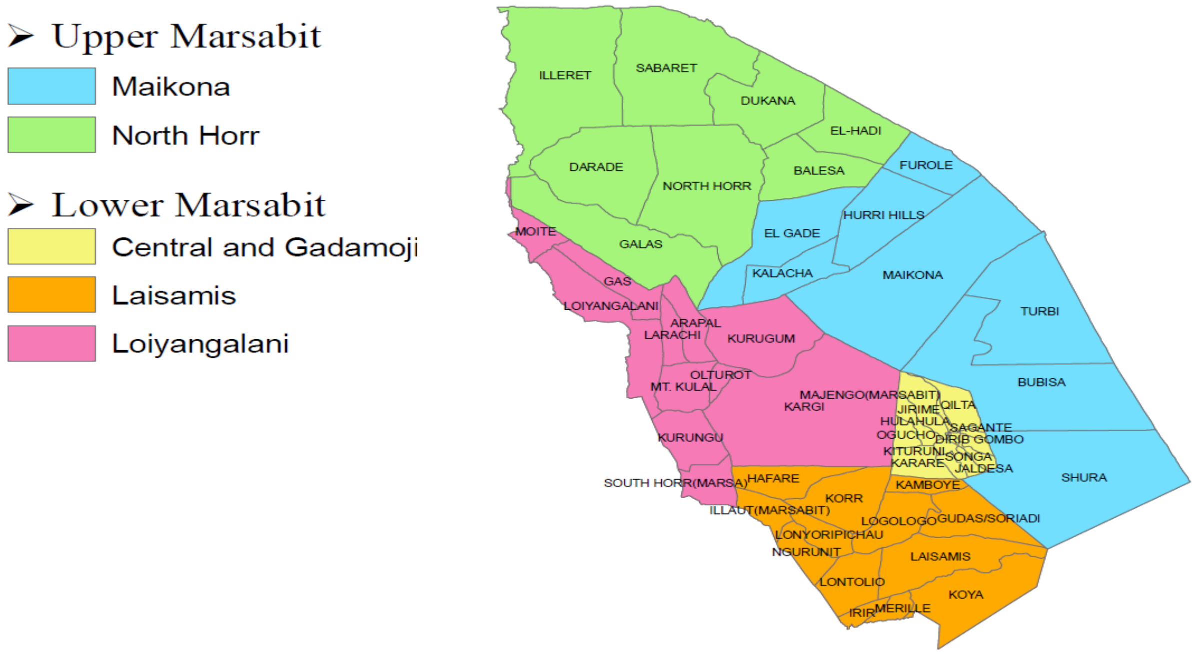

Figure 7 Study area in Marsabit District

Source: IBLI web site http://ibli.ilri.org

2.3.2 Data

Because the households in our study area face persistent shocks arising mainly from drought, it is most important to develop a clear understanding of livestock accumulation paths across households. To do so, we use panel data collected as part of the International Livestock Research Institute's (ILRI) Index-Based Livestock Insurance (IBLI) project, implemented in the Marsabit district of Northern Kenya, which administered a pre-intervention baseline survey in 2009 complemented by annual follow-ups from 2010 to 2015. For all these survey waves, information was collected in 16 sublocations (see Figure 7) using a sample proportionally stratified on the basis of the 1999 household population census. First, households are classified into three wealth categories based on livestock holdings converted into TLUs: low (<10 TLU), medium (between 10 and 20 TLU), and high (>20 TLU). Within each sublocation, one third of the location-specific sample was randomly selected from each of these wealth categories, which were then used to randomly generate a list of households. For replacement purposes additional households were randomly selected based on the wealth class that were to be used in case a household was to be replaced. For example, if a low, medium, or high wealth household cannot successfully be re-interviewed, it is replaced by an equivalent household during subsequent surveys, yielding a consistent sample of 924 households across all surveys. Our analysis uses the five survey waves (2009-2013).

In our analysis, we measure drought risk using remote sensing data from the NDVI (Normalized Difference Vegetation Index), a satellite-generated indicator of the amount of vegetation cover based on levels and amount of photosynthetic activity (Tucker et al. 2005). When the lack of sufficient rainfall reduces the levels of vegetative greenness, the lower NDVI values indicate forage scarcity. NDVI data are used not only in several studies that apply remote sensing for drought management (Rasmussen 1997; Kogan 1995; Unganai and Kogan 1998) but also by the IBLI, which is being implemented in Northern Kenya and Southern Ethiopia to provide a market-mediated livestock insurance among pastoralists (Chantarat et al. 2012). Research confirms that NDVI values are particularly reliable in arid and semi-arid areas with little cloud cover (Fensholt et al. 2006). The NDVI uses the intensity of photosynthetic activity to gauge the amount of vegetation cover within a given area. NDVI image data, which are available from the U.S. National Aeronautical and Space Administration (NASA), are gathered by a moderate resolution imaging spectroradiometer (MODIS) on board NASA's Aqua and Terra satellites (Tucker et al., 2005). These values are translated into a standardized NDVI Z-score, originally generated in designing the livestock insurance index for Northern Kenya (Chantarat et al. 2012), by computing the value for any pixel *i* of a 16-day *d* in year *t*:

$$zndvi_{idt} = \frac{ndvi_{idt} - E_d(ndvi_{idt})}{\sigma_d(ndvi_{idt})} \quad (9)$$

where $ndvi_{idt}$ is the NDVI image of pixel *i* for period *d* of year *t* and $E_d(ndvi_{idt})$ and $\sigma_d(ndvi_{idt})$ are the long-term mean and long-term standard deviation, respectively, of NDVI values for 16-day *d*s of pixel *i* taken over 2000–2009. Positive (negative) values represent better (worse) vegetation conditions relative to the long-term mean. As is evident, the NDVI is a good indicator of the extent of greenness – and thus the amount of vegetation – in a given area. Because livestock in pastoral production systems depend almost entirely on available forage for nutrition, the NDVI serves as a strong indicator of forage availability. It is also directly correlated with rainfall and hence considered a good measure of biomass productivity (Fensholt et al. 2006).

To ensure that our analysis accounts for such regional differences as agroecology, herd composition, and climatic patterns, we divide the study area into four regions: Central and Gadamoji, Maikona, Laisamis, and Loiyangalani[16] (see Figure 7). We then extract for these four regions the average ZNDVI values for the long rainy season (March, April, and May) in each survey year, allocating to each household the annual NDVI Z-score for its respective region (Chantarat et al. 2012).

2.4 Descriptive statistics

The descriptive statistics for our key variables (see Table 13) show a declining trend in the number of livestock owned (represented by TLUs) between 2009 and 2013. This decline is more pronounced from 2011 onward, possibly because of drought experienced in 2009 and 2011. The average family has six members, while the average age of the household head is about 50 years. The uptake of livestock insurance is highest in 2010 (26.3%) but then declines at an overall mean rate of 13.6% of the uptake. Herd migration is quite common, with an average of 72.4% households moving their livestock in the 2009–2013 period. This migration enables pastoralists to respond to changes in forage and water availability at different times across rangelands. One aspect that shows an increase over time is membership in women's groups, which enable members to save and borrow money for household needs such as food and school fees. In terms of other assistance, more households are receiving cash aid than food aid, although with an increase in both types in the drought

[16] The North Horr region is not covered in the household survey and is thus excluded from our analysis.

years of 2009 and 2011. The mean livestock diversity remains quite constant, indicating that households kept the same types of animals over the study period.

Table 13 Summary of key household characteristics

Key variables	Full	2009	2010	2011	2012	2013
TLUs	13.8	16.1	16.5	11.5	11.9	12.7
Age of head (years)	48.8	47.9	47.7	48.5	49.5	50.4
Household size	5.9	5.6	5.7	5.6	6.4	6.4
Have livestock insurance (%)	13.6	0.0	26.3	24.4	8.7	8.8
Moved livestock[a] (%)	72.4	63.2	76.7	72.7	75.6	74
Belong to women's group[b] (%)	35.9	28.7	34.7	38.1	37.6	40.8
Receiving food aid (%)	8.3	8.5	4.8	18.5	6.5	3.4
Receiving cash aid (%)	32.6	20.9	26.1	33.7	48.1	34.6
Herd diversity index[c]	0.38	0.37	0.36	0.39	0.38	0.38
ZNDVI long rains[d]	-0.05	-0.75	0.61	-0.78	0.27	0.42

Notes: Results are based on IBLI data for a consistently sized sample of 924 households
[a] Percent of households that migrated their livestock in search of grazing pastures
[b] Percent of households with a member belonging to a women's group
[c] Shannon-Weiner Diversity Index
[d] ZNDVI is the standardized normalized difference vegetation index for the long rain season (March-May season) for each year

The average herd diversity index is 0.38 for the full sample based on a range from one, high diversity, to zero, no diversity. In both 2009 and 2011, the study area suffered major drought whose severity is reflected by the low NDVI Z-scores for those years. The notable improvement in NDVI Z-scores since 2012, on the other hand, indicates improved forage availability in the rangelands. The mean TLUs of livestock owned during the survey period, shown in Table 14, indicate consistently declining ownership, which implies that the households were becoming steadily livestock poorer over time. Given that livestock is the key productive asset among the surveyed households, this consistent decline means diminishing wealth and standard of living, especially when non-livestock economic opportunities are limited. Further disaggregation of livestock owned by sublocation reveals that households in the Sagante, Dirib Gombo, and Loiyangalani sublocations have the smallest herd sizes.

Table 14 Mean TLUs of livestock owned during the survey period

Survey period	Camels	Cattle	Sheep/goats
2009	7.1	4.5	4.6
2010	7.7	3.8	5.1
2011	6.4	2.3	3.1
2012	6.3	2.5	3.4
2013	6.4	2.9	3.6

Note: The TLUs are computed for each animal species from all households owning livestock at the time of each survey, which numbered 854, 859, 858, 869, and 860, respectively.

The livestock data also reveal interesting trends in the drivers of livestock accumulation and de-accumulation across the survey period. Specifically, they show rather low livestock offtake transactions, with the sales of sheep and goats being more common because they are easier to sell for ready cash to meet urgent household needs. The reasons for livestock sales are varied: a need for cash income (46.1%), as a coping strategy in times of drought (38.5 %), and/or for cultural reasons such as dowry (5.0%). The highest livestock losses are recorded for sheep and goats, especially in 2011, whereas camels, being more adapted to drought conditions and more able to withstand prolonged dry periods, are least affected. Livestock losses are mainly attributable to death from drought or starvation (45.7%), disease (31.1%), or predation (10.4%). The number of cattle taken off and the number lost have a positive correlation coefficient of 0.30, indicating that offtake and sales occur simultaneously. This latter may indicate that households sell cattle mostly as a coping mechanism when faced with the risk of losing their herd, especially during drought periods. Similarly, few animals are slaughtered, except in 2011 when more sheep and goats are slaughtered than other livestock types. The main reasons for slaughtering are home consumption (42.3%) and ceremonies (41.1%), with only 8% slaughtered for sale (mostly camels and cattle). Households obtain livestock in various ways: as gifts (47.7%), purchases (19.1%), loans (18.7%), or dowry payments (7.7%). After losing animals, usually from drought or disease, households borrow mainly female animals from relatives or friends in the community. They benefit from the milk but are expected to return the animal upon calving or after a certain period. The main reasons for livestock intake are expanding stock (46.0%), restocking after losses (15.0%), or as a traditional or cultural right (14.1%). As expected, more sheep and goat births are reported than cattle or camel births because of the shorter gestation period. These livestock births make the highest contribution to livestock accumulation (approximately 80% in all rounds), with livestock intake in the form of purchases or gifts contributing little (about 20%). Natural reproduction is thus the main driver of herd accumulation, which could explain the slow growth in herd size over the study period given that calving is affected by both the animals' condition and forage availability. Livestock de-accumulation is mainly attributable to losses from starvation or disease fatalities, which at 70% is highest in the drought year of 2011. In fact, the data indicate that starvation and disease account for 47% and 30.5% of livestock losses, respectively. Moreover, although livestock offtake is relatively low, it does show an increase from 20% in 2011 to 40% in 2013. Given the low rate of livestock slaughter, livestock losses must necessarily be the dominant factor in these diminishing livestock trends.

2.5 Methodology

Because our primary research interest is in assessing the relation between past and future assets (expressed as TLUs), we estimate a function of the following form:

$$A_{it} = f(A_{it-n}) + \epsilon_{it} \tag{10}$$

where A_{it} represents household *i*'s assets at time period *t*, A_{it-n} represents the lagged assets, and ϵ_{it} is the error term that is normally distributed with a zero mean and constant variance. In estimating Equation (10), we use both nonparametric and semiparametric methods to allow for a nonlinear relation between current and lagged assets. One important assumption for these estimations is that all households have the same underlying asset accumulation path.

2.5.1 Nonparametric estimations

Nonparametric estimation involves fitting a function to the data that is assumed to be smooth and have covariates that are uncorrelated with the error term. This error term is in turn assumed to be normally and identically distributed with an expected value of zero. We employ the locally weighted scatterplot smoother (LOWESS), also used by Lybbert et al. (2004) and Barrett et al. (2006) in their dynamic asset equilibrium analyses, a method attractive for its use of a variable bandwidth and its robustness to outliers, which minimizes boundary problems (Cleveland 1979; Cameron and Trivedi 2009). LOWESS performs a locally weighted regression of two variables and displays the plotted graph.

2.5.2 Semiparametric estimations

We find it necessary to add semiparametric estimation into our analysis because both parametric and nonparametric estimation techniques have limitations. Whereas parametric specifications have difficulty identifying unstable points in areas with few observations and need large samples if fitted polynomial functions are to accurately reflect the few observations around the thresholds, nonparametric estimation is limited in how much it can control for (Naschold 2013). Semiparametric techniques, in contrast, have a flexible functional form for asset path dynamics and can also control for other variables linearly. We represent our semiparametric model as follows:

$$A_{it} = \beta_0 + f(A_{it-n}) + X_{it}\beta_1 + N_{it}\beta_2 + T_i\beta_3 + R_i\beta_4 + \epsilon_{it} \qquad (11)$$

where A_{it} represents household i's current TLUs owned, A_{it-n} its lagged TLUs owned, and X_{it} the control variables: age of household head, household size, a dummy for membership in a women's group, and a dummy for households purchasing livestock insurance during the survey period. Because diversifying herds is an important risk minimization strategy for pastoralists (i.e., mixing small and large stock optimizes grazing pasture use), we include an additional control variable derived from the Shannon-Weiner Diversity Index[17] that captures both species dominance and evenness (Achonga et al. 2011). This index, which ranges from zero, no diversity, to one, high diversity, yields an average of 0.38. Here, N_{it} represents the average ZNDVI values for the long rainy season in each year; T_i represents the time period dummy, R_i the regional dummy, and ϵ_{it} the error term. The X_{it}, N_{it}, and T_i variables are estimated linearly, whereas the relation between assets (A_{it}) and lagged assets (A_{it-n}) is estimated non-parametrically. We also use the Hardle and Mammen (1993) test to determine whether the polynomial adjustment is of 1 or 2 degrees.[18] Specifically, to check the robustness of the changes in livestock assets over time, we estimate a fourth-order polynomial regression of the lagged assets while controlling for household, regional, and time-specific variables:

$$A_{it} = \beta_0 + f(A_{it-1}) + (A_{it-1})^2 + (A_{it-1})^3 + (A_{it-1})^4 + X_{it}\beta_1 + N_{it}\beta_2 + T_i\beta_3 + R_i\beta_4 + \epsilon_{it} \quad (12)$$

Although the TLUs are greater than 100 in a few cases, for this analysis, we consider them outliers and thus exclude them to obtain a clear asset path. These excluded cases represent less than 1% of the entire sample.

2.6 Results and Discussion

2.6.1 Nonparametric results

The nonparametric estimations for the locally weighted scatter plot smoother (LOWESS) are graphed in Figure 8, which shows trends in 2009 and 2013 for a one-year and four-year lag, respectively. The curves of both these lags intersect the 45° line only once, indicating only one stable equilibrium to which household livestock accumulation converges. The one-year lag

[17] $H = -\sum_{i=1}^{r} p_i ln p_i$ After calculating the proportion of livestock species *i* relative to the total number of species TLUs (p_i), we multiply it by its natural logarithm (lnp_i), sum the resulting product across species (camel, cattle, sheep, and goats), and multiply it by -1.

[18] Hardle and Mammen (1993) suggest the use of simulated values obtained by wild bootstrapping, in which inability to reject the null (i.e., acceptance of the parametric model) means that the polynomial adjustment is at least of the degree tested. We reject the null hypothesis ($p < 0.05$) for the two tests and thus accept the use of the semiparametric model.

curve intersects the 45° line at around 18 TLUs, while the four-year lag curve does so at a lower level (15 TLUs).

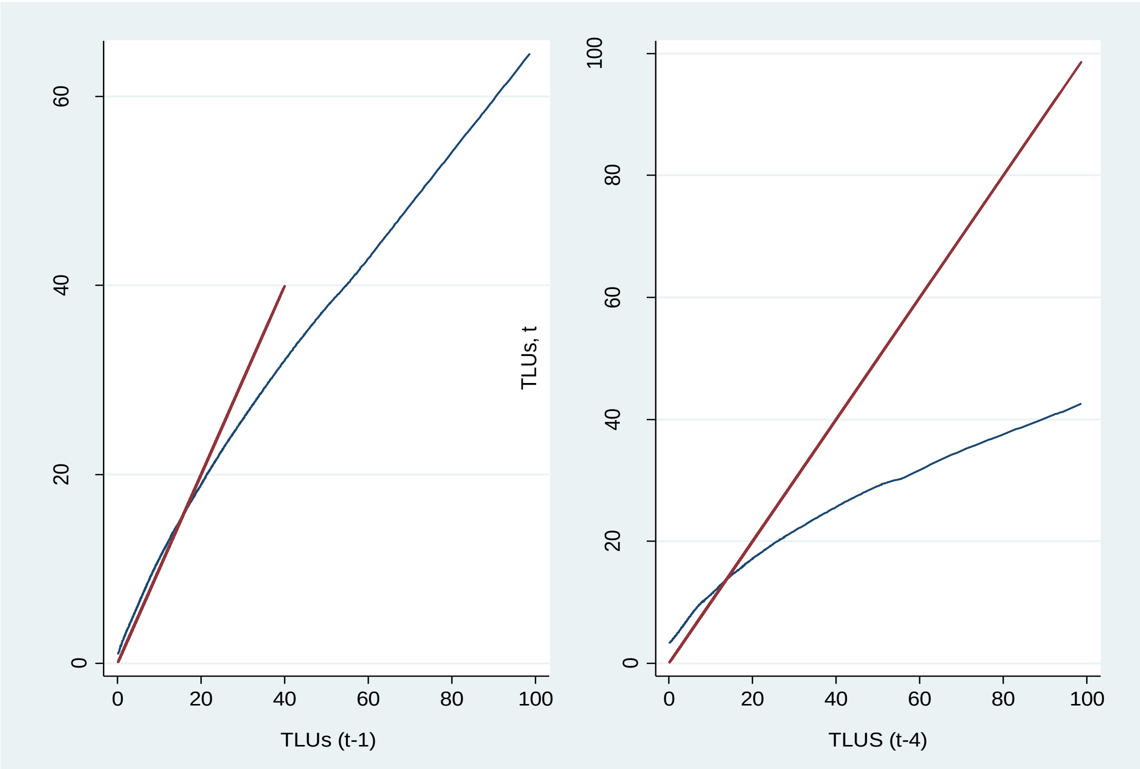

Figure 8 Nonparametric estimation of lagged TLU dynamic path (one-year and four-year lags

Because the nonparametric estimation does not control for covariates that could also influence asset accumulation, we use a semiparametric estimation to take such factors into account (see Figure 9). After controlling for other key covariates, the stable equilibrium decreases to around 10–13 TLUs at the lower confidence interval with a slope that is flatter than in the nonparametric case. As Figure 9 clearly illustrates, we observe one single equilibrium,[19] a converging path that may partly reflect contrasting household strategies. That is, whereas livestock endowed households faced with limited credit access tend to smooth consumption during food shortages by selling or slaughtering livestock, livestock poor households use such coping strategies as meal reduction or rely more on food aid rather than

[19] Re-running the analysis using two-year and three-year lags does not change the results: the estimated curves show only a single dynamic equilibrium.

depleting their already small livestock holdings. This interpretation is in line with Hoddinott's (2006) finding that poorer households, when faced with income loss, tend to preserve their few animals to ensure a future herd while those with more livestock smoothen consumption through livestock sales or slaughter for home consumption. Similar findings are reported by Giesbert and Schindler (2012) and Carter et al. (2007).

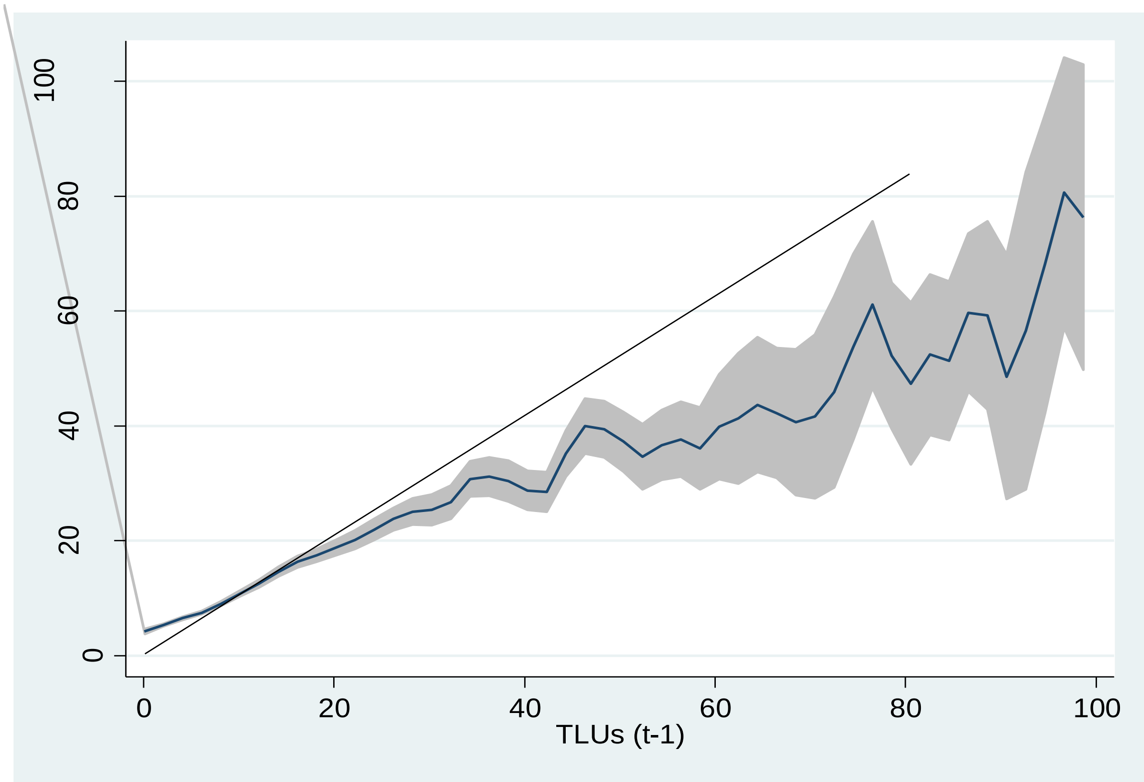

Figure 9 Semiparametric estimation of TLU-based dynamic path

To better understand the livestock assets convergence path, we look at how households actually cope during times of food shortage. We specifically examine the proportion of households that sell or slaughter livestock during times of food shortage. Our results show that 37.2% of the households sell livestock, 39.9% reduce the number of meals, and 5.8% increase non-livestock activities. These responses are in line with the predictions of our theoretical model that following a shock, both consumption and livestock holdings will decline. Interestingly, households that sell livestock as a primary coping strategy own more livestock (an average of 20.1 TLUs), while households that reduce the number of meals or increase the number of non-livestock activities own fewer animals (an average of 9.7 TLUs and 5.9TLUs, respectively).

2.6.2 Semiparametric and polynomial estimates

The semiparametric and polynomial regression coefficient estimates are presented in Table 15, which shows that the average NDVI Z-score for the long rainy season have a positive and statistically significant effect on livestock accumulation. More specifically, in the parsimonious model, a one standard deviation increase in NDVI Z-score leads to a 2.76 increase in TLUs, although this effect declines slightly to 2.46 TLUs once we control for other covariates. Herd diversity is also positive and statistically significant: a one unit increase in herd diversity leads to a 4.8 unit increase in TLUs, a figure that changes little when other covariates are controlled for. Evidently, by keeping different livestock species in their herd, pastoralists can manage risks like drought and optimize grazing pastures more fully. More specifically, small livestock like sheep and goats can browse well in areas with minimal pastures, while camels can survive better during prolonged periods of drought.

Although the index-based livestock insurance offered enables households to mitigate risks related to livestock deaths from drought, its effect is positive but not significant, perhaps because of the low number of households insured. Households in Loyangalani region are worse off than households in the Central and Gadamoji region. The coefficients for all survey years are negative (although only significant for wave two), indicating a consistent decline in livestock owned over the five-year period. The polynomial estimates are quite similar to the semiparametric results, with a significantly negative lagged cubed TLU that indicates diminishing marginal returns to assets. The predicted curve for the fourth-degree polynomial regression is shown in Appendix 4.

Table 15 Factors influencing livestock accumulation over time

	(1) Semiparametric	(2) Semiparametric	(3) Polynomial
ZNDVI (long rains)	2.7613***	2.6997***	2.7961***
	(0.301)	(0.308)	(0.315)
Herd diversity index		5.0742***	4.9392***
		(0.616)	(0.608)
Household size		0.0502	0.0406
		(0.073)	(0.075)
Have insurance (1 = yes)		0.0057	0.0446
		(0.401)	(0.405)
Belong to a women's group (1=yes)		0.4916	0.4427
		(0.329)	(0.334)
Receive food aid (1=yes)		-0.5238	-0.4301
		(0.627)	(0.629)
Receive cash aid (1=yes)		-0.3617	-0.3372
		(0.327)	(0.332)
Lagged TLU			0.8327***
			(0.111)
Lagged TLU squared			0.0067
			(0.008)
Lagged TLU cubed			-0.0003*
			(0.000)
Lagged TLU quadruped			0.0000**
			(0.000)
Constant			-0.4365
			(0.577)
N	3197	3196	3196
Adj. R^2	0.028	0.047	0.617

Note: Robust standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01. Region and time dummies are estimated but not shown.

Because we also recognize that despite the rich set of covariates in our dataset, certain important characteristics might still be unobservable, we exploit the longitudinal nature of the data by also including a fixed effects model to account for time-invariant individual characteristics (see Table 16). The models within transformation also eliminates invariant unobservables that might be correlated with our covariates of interest.

Table 16 Fixed effects regression estimates of factors influencing livestock accumulation

	(1) FE	(2) FE	(3) FE
ZNDVI (long rains)	0.5124***		0.8194***
	(0.190)		(0.219)
Herd diversity index		6.8349***	6.9992***
		(1.212)	(1.214)
Household size			-0.4784**
			(0.220)
Have insurance (1 = yes)			-0.0945
			(0.401)
Belong to a women's group (1 = yes)			-0.7611
			(0.464)
Receive food aid (1 = yes)			-0.3968
			(0.548)
Receive cash aid (1 = yes)			-1.3859***
			(0.343)
Constant	13.8212***	11.0405***	17.2954***
	(0.008)	(0.489)	(1.375)
N	4258	4258	4257
Adj. R^2	0.001	0.016	0.039

Note: Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Region and time dummies are estimated but not shown

The results of the fixed effects model support the semiparametric regressions. Herd diversity and NDVI Z-score are positive and significant with minimal change when other covariates are controlled for. We also note that cash aid received is negative and significant, which could be interpreted as reverse causality in that cash aid tends to go to households with few livestock. Household size is also negative and significant, perhaps because larger families sell or slaughter more livestock than smaller families. The regression analysis also implies that forage availability as proxied by NDVI Z-score and herd diversity is a key determinant of livestock accumulation among pastoralists.

2.7 Conclusions

The livestock dynamics of pastoral households are especially important because of the disrupting influences of regular and severe droughts in the study area. According to the microeconomic model developed in this study, such droughts negatively affect both livestock holdings and consumption. The model also indicates that the adjustment of capital, consumption, aid, and wages back to the long-term steady state equilibrium takes longer than the transition of internal and external labor supply. Our results also reveal that, in contrast to the case of low volatility, higher shock volatility does not necessarily lead to an increase in the number of periods with very low capital accumulation and low levels of consumption. This observation is in line with the theoretical model that shows that pastoralists only greatly increase their participation in external labor when volatility is high and the economic cycle, peaking. In other circumstances, they tend to concentrate primarily on tending their own livestock.

Our nonparametric and semiparametric analyses also point to the existence of a single equilibrium, although the semiparametric penalized splines which control for other covariates that affect livestock accumulation produces lower equilibria values than the nonparametric results. As previously stressed, such convergence to a stable equilibrium could result from households with more livestock smoothening their consumption during times of food shortage by drawing on their herds for sale or consumption while livestock poor households smoothen their assets by using coping strategies such as relying more on food aid or reducing the number of meals that do not deplete their few livestock holdings. Poor households thus destabilize their consumption to buffer and protect their few assets for future income and survival. These results also imply that forage availability and herd diversity influence livestock accumulation over time.

Although these findings are similar to those in several studies on asset dynamics and poverty traps (Naschold 2012; Mogues 2004; Quisumbing and Baulch 2009), other studies based on pastoral livestock holdings identify multiple equilibria (e.g., Barrett et al. 2006; Lybbert et al. 2004). These latter, however, cover much longer time lags (13 and 17 years, respectively) suggesting that our five-year interval may simply not be long enough to illustrate long-run livestock dynamics given the slow changes observed in livestock assets. This possibility apart, the consistently declining livestock trends and few options for livestock intake available among the households in our sample support the notion of a movement toward a single low-level stable equilibrium. Such a conclusion is also in line with Lybbert et al.'s (2004) evidence that to sustain mobile pastoralism on the East African rangelands, a household should have at least 10–15 animals. In our study, only 30% of the households have a herd size of more than 15 animals, suggesting that the majority of households surveyed have difficulty reaching a sustainable herd size.

In the presence of the single low-level stable equilibrium observed here, household asset poverty can only be alleviated through structural change that raises the equilibrium asset level. Ways to effect such change include interventions that raise the returns to existing assets and the provision of a broad range of productive assets that eventually raise the level of the welfare equilibrium. In addition, because accumulation of livestock in the study area is greatly hindered by drought, households should be supported in strengthening their risk management mechanisms against negative shocks. Our findings also suggest that implementing welfare enhancing measures such as safety nets and forage conservation is crucial to lifting these poor households out of asset poverty.

Chapter Three: Effects of Drought on Child Health in Marsabit, Northern Kenya

Abstract

Because weather-related shocks are a threat to the health of the most vulnerable, this study uses five years of panel data (2009–2013) for Northern Kenya's Marsabit district to analyze the levels and extent of malnutrition among children aged five and under in that area. In doing so, we measure drought based on the standardized normalized difference vegetation index (NDVI) and assess its effect on child health using mid-upper arm circumference (MUAC). The results show that approximately 20 percent of the children in the study area are malnourished and a one standard deviation increase in NDVI *z*-score decreases the probability of child malnourishment by 12–16 percent. These findings suggest that remote sensing data can be usefully applied to develop and evaluate new interventions to reduce drought effects on child malnutrition, including better coping strategies and improved targeting of food aid.

Key words: climate change, child health, pastoralists, livestock

3.0 Introduction

Weather-related shocks are a serious global threat that increasingly affect lives across the globe (Stern, 2006). Particularly in developing countries, people are most likely to suffer negative health outcomes as they tend to rely on locally produced food, lack access to proper health care, and are often in a vulnerable state of health even before experiencing weather shocks (Xu et al., 2012; FAO 2015). Yet whereas the health implications of such shock events as flooding, heat waves, and wildfires are relatively well studied, evidence for the more complex link between drought and health outcomes remains limited (Stanke et al., 2013). For example, with no clear-cut triggering event, the onset of a drought is hard to identify because the absence of sufficient rainfall is a slowly emerging process (Opiyo et al., 2015). Nonetheless, many families depending on rural livelihoods remain vulnerable to extreme weather conditions and their negative effects, with drought risk at the forefront (Garnett et al., 2013). One recent study estimates that drought has affected three times more people in Africa than all other natural disasters combined (Dinkelman, 2015).

One population at particularly high risk for malnutrition and mortality is young children and infants, who are more vulnerable to weather shocks (Xu et al., 2012). Child malnutrition is an important issue in the Marsabit district of Northern Kenya, in whose remote hotspots one of four children are malnourished (UNICEF, 2013). This district, which is predominantly inhabited by pastoralists, is an arid region prone to frequent droughts that result in food shortages and hunger that lead to child malnutrition. Hence, to assess whether and to what extent drought affects child health despite the ongoing presence of food aid, this study analyzes the relation between drought and the nutritional status of children in Marsabit district. Specifically, the two main study objectives are to identify the levels and extent of child malnutrition in the study area and to estimate the effects of drought on child health outcomes. Given the minimal previous exploration of drought's effect on child health in this area, we hope that the results can guide future interventions and improve the targeting of the most vulnerable children.

Although previous studies have addressed the relation between weather shocks and household food security (e.g. Xu et al., 2012; Stanke et al., 2013; Phalkey et al., 2015), much of this literature is hampered by relatively small sample sizes and its inability to identify causal relations (Phalkey et al., 2015). Furthermore, adverse drought-related health effects are sensitive to local coping mechanisms, drought intensity, health infrastructure, and individual characteristics (Brown et al., 2014). All of these factors differ among regions and cultures, thereby making it difficult to generalize previous findings. Our contribution to the literature is thus to provide an analysis for the Marsabit district using unique household panel data and satellite information which, in comparison to much of the previous literature, allows us to better identify causality.

3.1. Previous literature

In Kenya, child mortality and malnutrition remain high despite the government's commitment to creating a facilitative environment for quality health care provision and reducing mortality and malnutrition levels. According to the Kenya National Bureau of Statistics (KNBS, 2015), the under-five mortality in Kenya is well above 39 deaths per 1,000 births albeit with a declining trend that is partly attributable to the increase in malaria prevention (Demombynes and Trommlerová, 2016). Between 2008 and 2013, 35.3 percent of children under five were stunted, 6.7 percent were wasted, and 4 percent were severely underweight (UNICEF, 2013). Nevertheless, the prevalence of child malnutrition varies within the country: children in the arid and semi-arid areas, particularly, suffer from growth deficiency and are more likely to die at a young age (Government of Kenya, 2014a).

Weather shocks like drought lower health through two primary channels: insufficient food intake and weather-related diseases (Skoufias and Vinha, 2012), with the well-documented link between drought and child health (Alderman et al., 2006; Hoddinott and Kinsey, 2001; Xu et al., 2012) associated with water-, air-, and vector-borne diseases (Stanke et al., 2013). Low water availability, in addition to possibly increasing water pollution and reducing hygienic practices (Moran et al., 1997), may be accompanied by respiratory conditions through increased dust exposure. Evidence for vector-borne diseases like malaria, however, remains ambiguous. Although drought often leads to reduced infection, migration as a response to drought and the death of mosquito predators can amplify vector-borne diseases. Pastoralists in sub-Sahara Africa are at particular risk for diseases like tuberculosis, anthrax, diarrhea, and trachoma, all of which are compounded by undernutrition (Fratkin et al., 2006).

The most prominent effect of drought on human health, however, is malnutrition (Phalkey et al., 2015). Already prenatal drought experience can affect the health of the yet unborn child. High temperature and low precipitation is found to increase the probability of low birth weight among African's newborns (Grace et al., 2015). Such adverse health effects often persist, as shown in a study of Kenyan and Ethiopian children born in drought years; such children were more likely to remain malnourished up until the age of six (Araujo et al., 2012; Xu et al., 2012).

The nutritional status of children in Africa is strongly linked to weather shocks (Alfani et al., 2015) and children exposed to drought not only show less body weight, but also suffer from growth retardation. In Zimbabwe, for instance, drought experienced by children between 12 and 24 months lowered the annual growth rate, leading to a 1.5 to 2 cm lower average height of children four years and older compared with children of the same age in previous years (Hoddinott and Kinsey, 2001). Ethiopian children between 6 and 24 months also experienced 0.9 cm lower growth over a six-month period in regions where half the crop area was affected by drought (Yamano et al., 2005). Similarly, drought exposure during early childhood can have long lasting effects and is linked to a 4 percent higher disability rate among South African adult males (Dinkelman, 2013).

When looking at particular child characteristics[20], the short term effects of drought may differ by child gender, with girls often less affected than male siblings (Araujo et al., 2012; Grace et al., 2012). Some studies (e.g. Hoddinott and Kinsey, 2001) also show that drought has fewer adverse effects when experienced later in life. Nevertheless, other researchers show that the youngest children are better off because of either preferential dietary access (McDonald et al., 1994) or highly nutritious breast milk (Asenso-Okyere et al., 1997).

The important role played by milk in the diet of Africa's children is highlighted in several studies comparing sedentary and active pastoralist communities. On average, the children of pastoralists are uniformly taller and heavier than the children of more sedentary families (Nathan et al., 1996; Fratkin et al., 2004; Pedersen and Benjaminsen, 2008). These analyses, two conducted in Kenya, imply that access to milk is a major determinant of child health regardless of current drought levels. Similarly, Fujita et al. (2004) demonstrate a decline in

[20] See Phakley et al. (2015) for a recent review of subsistence farmers in low and middle-income countries.

health and nutritional status among settled agriculturalists relative to Rendille pastoralists in Ariaal communities in Northern Kenya. Child malnutrition not only affects physical health but also human capital formation, as when drought affected children in Zimbabwe not only experienced stunted growth but also performed more poorly in school (Alderman et al., 2006). Children often do not fully recover from drought events, and the detrimental effects on human capital translate into overall lower lifetime earnings (Dercon and Hoddinott, 2003).

As implied by the above discussion, the effect of drought on child health must be clearly understood to guide interventions and evaluate their performance (Xu et al., 2012). Understanding this relation, however, requires reliable forecasting and full comprehension by intervention planners of the link between severe weather conditions and child nutritional status. Rainfall and temperature, particularly, are often used as drought indicators because of their importance in agricultural productivity for crop yields (e.g., Skoufias and Vinha, 2012). The extremes of both rainfall (flood or drought) and temperature (too hot or too cold) can have negative effects on livestock and crop yields, thereby affecting the amount of food available for consumption by rural households. Hence, to identify the effect of weather shocks in Burkina Faso, Araujo Bonjean et al. (2012) estimate rainfall's effects on child health at various ages by calculating the cumulated rainfall deviation from the annual normal average for different study sites. Another tool that has gained popularity in recent drought research is the normalized difference vegetation index (NDVI), a satellite-generated indicator of vegetation cover based on levels and amount of photosynthetic activity (Tucker et al., 2005), which is used to measure drought risk. When the lack of sufficient rainfall reduces vegetative greenness, the correspondingly lower NDVI values indicate forage scarcity. In addition to being used in several studies that apply remote sensing for drought management (Kogan, 1995; Rasmussen, 1997; Unganai and Kogan, 1998; Roy Chowdhury, 2007), NDVI data are the basis for drought warnings from the Famine Early Warning Systems Network (FEWSNET)[21]. NDVI has also been used for drought risk estimation by the Index Based Livestock Insurance (IBLI) Project, which provides market-mediated livestock insurance among pastoralists in Northern Kenya and Southern Ethiopia (Chantarat et al., 2012). NDVI values are shown to be particularly reliable in arid and semi-arid areas with little cloud cover (Fensholt et al. 2006). For example, Brown et al. (2014), using data for four West African countries (Burkina Faso, Mali, Guinea, and Benin), documents a negative association between NDVI values and child wasting. They also show, however, that the effect of weather shocks on household food security is sensitive to the coping response of both households and governments. They therefore conclude that the existence of an adequate safety net for the poor could impede any significant relation between NDVI and child health. Developing an empirical forecasting model, Mude et al (2009) use NDVI as a key proxy for forage availability to predict the effect of covariate shocks on the nutritional status of children in Northern Kenya. The study finds NDVI, food aid flows, and lagged herd composition to predict child nutritional status with good precision. The study, however, was limited by a lack of longitudinal micro-data and was therefore conducted with aggregated data at the community level.

According to recent studies (e.g. Xu et al., 2012; Phalkey et al., 2015; Grace et al., 2015), more research is needed to improve the understanding of weather-related shocks on the health of children. We contribute to the existing literature by using NDVI as a reliable measure of drought (Brown et al., 2014) in combination with five years of household panel data from the remote Marsabit district, an area distinct from the rest of Kenya (Grace et al., 2014). An analysis of this particularly drought prone district provides valuable insights into the vulnerability of children to weather changes and the effectiveness of ongoing food aid programs in mitigating this relationship. Locally measured drought indicators are often incomplete (see e.g. Skoufias

[21] For further information, see http://earlywarning.usgs.gov/fews

and Vinha, 2012) and missing data might correlate with local health conditions. We overcome this possible source of bias by using remote sensing data (NDVI) as a drought indicator. Combining NDVI with household panel data is an additional strength of this study. This allows estimating an indirect but (close to) causal effect of drought on child health, as we are able to account for unobservable characteristics that could potentially confound our estimates (Alfani, 2015).

3.2 Study Area and Data

3.2.1 Study area

The Marsabit district is characterized by an arid or semi-arid climate (rainfall of up to 200 mm/year in the lowlands and 800 mm/year in the highlands), droughts, poor infrastructure, remote settlements, low market access, and low population density (approximately 4 inhabitants per km^2). This area, which covers approximately 12 percent of the national territory, is home to approximately 0.75 percent of the Kenyan population and encompasses several ethnicities—including Samburu, Rendille, Boran, Gabra, and Somali—each with distinct languages, cultures, and customs. These pastoral communities live in semi-nomadic settlements in which livestock, the main source of livelihood, is moved across vast distances in search of grazing pastures, especially during the dry season. Largely dependent on milk from livestock (mainly camels or cattle) for home consumption, these communities also trade or sell animals (primarily goats and sheep) to purchase food and other commodities (Fratkin et al., 2005). In our study, we analyze data for 16 sub-locations distributed across the Marsabit district, which in Fig. 10 is color coded into five broader regions based on similar agro-ecological conditions, herd composition, and climatic patterns (ILRI, 2012).

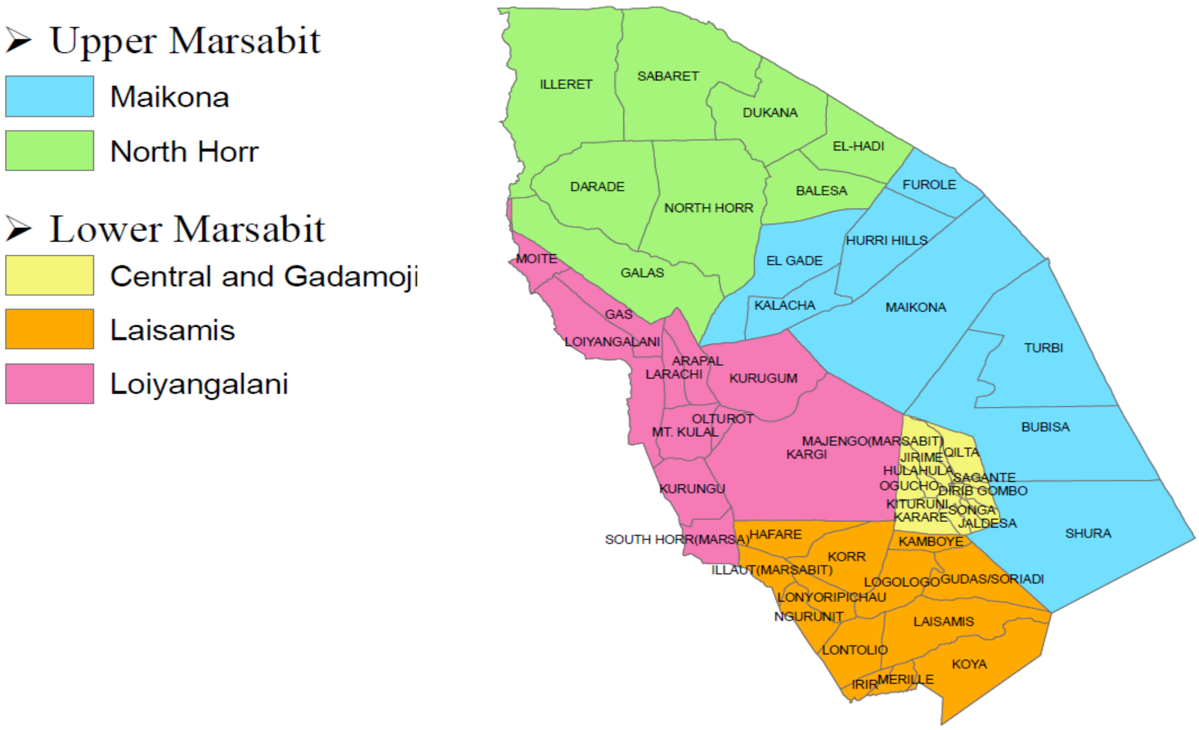

Figure 10 Study Area in Marsabit District

Source: IBLI web site http://ibli.ilri.org

3.3 Data

The data for this study are taken from two different data sources: (i) NDVI remote sensing data, which proxy drought risk and (ii) IBLI child and household panel data, used to assess child health and regional variation.

3.3.1 Normalized Difference Vegetation Index

The NDVI uses the intensity of photosynthetic activity to gauge the amount of vegetation cover within a given area. NDVI image data, which are available from the U.S. National Aeronautical and Space Administration (NASA), are gathered by a moderate resolution imaging spectroradiometer (MODIS) on board NASA's Aqua and Terra satellites (Tucker et al., 2005). The global data set, with a resolution of 8 km * 8 km, is available every 16 days with possible values between -1 and 1. Higher values indicate a higher level of greenness and reflect the amount of forage available to pastoralists and their livestock.

We apply the NDVI data for two reasons: First, NDVI values are exogenous to the household and community factors that affect child health and correlate directly with rainfall (Fensholt et al., 2006). Second, in a pastoral context, the condition of the rangelands reflects household food availability. When forage is plentiful, more milk and meat are available for consumption, but in dry periods, milk and food are in short supply, which negatively affects child health. Hence, the use of the NDVI is conceptually convincing and should clearly illustrate any effect of weather variability on child health. For analytic convenience, we transform the pure NDVI values to a *z*-score (cf. Chantarat et al., 2012):

$$zndvi_{ptd} = \frac{ndvi_{ptd} - \frac{1}{n}\sum_{i=1}^{n} ndvi_{pd}}{S_p(ndvi_{pd})}$$

Here, we calculate the $ndviz_{ptd}$ by subtracting the long-term mean from the pure NDVI values of pixel *p,* a 16-day dekad[22] *d,* and year *t.* This mean is calculated from the historical NDVI values for pixel *p,* in dekad *d,* over *n* observations between 2000–2009. These values are divided by the long-term standard deviation (*SD*) of the NDVI to obtain a *z*-score (see Chantarat et al. 2012). All pixels comprise an average NDVI *z*-score for the respective region and dekad. This transformation facilitate interpretation because values that deviate from zero, the long-term mean, can be interpreted as an *SD* from the average long-term greenness in the respective area. The *z*-score also adjusts the NDVI values for local characteristics, aggregated for each of the five broad regions, to obtain a coherent measurement relative to the normal drought condition (Chantarat et al., 2012).

It should be noted, however, that because our household survey data do not cover the North Horr regions, the analysis includes only Central and Gadamoji, Maikona, Laisamis, and Loiyangalani (see the NDVI scatter plot and MUAC regional average *z-scores* in Figure 12)

[22] Although originally coined to refer to 10-day intervals, the meteorological term "dekad" is now applied to various periods within the 8–16 day range needed by MODIS's cloud-screening algorithm to counter the effects of atmospheric contamination (clouds and aerosols).

Specifically, we use the average NDVI *z*-score values from the long dry season (June, July, August, and September) in each survey year, extracted for these four regions. The end of this dry season also coincides with the time of survey administration, which enables us to capture the levels of child wasting more accurately.

3.3.2 Household survey data

The panel data on child health and household characteristics are obtained from the IBLI, which, starting in 2009, annually surveyed 924 households in Northern Kenya's Marsabit district with follow-ups conducted until the latest survey wave in 2013. These data were collected in 16 sublocations[23] using a sample that was proportionally stratified based on the 1999 household population census. Initially, households were classified into three wealth categories based on livestock holdings converted into TLUs[24]: low (<10 TLUs), medium (between 10 and 20 TLUs), and high (>20 TLUs). Within each sublocation, one third of the location-specific sample was randomly selected from each of these wealth categories, which were then used to randomly generate a list of households. For replacement purposes additional households were randomly selected based on the wealth class that were to be used in case a household was to be replaced. For example, if a low, medium, or high wealth household could not successfully be re-interviewed, an equivalent household replaced it during subsequent surveys, yielding a consistent sample of 924 households across all five survey waves. The data set contains a rich set of individual and household characteristics, including anthropometric data for children under five.

We proxy child nutritional status by mid-upper arm circumference (MUAC), whose ability to capture short term changes in wasting make it a good measure of child health variation due

[23] The 16 sublocations are Dirib Gombo, Sagante, Dakabaricha, Kargi, Kurkum, Elgathe, Kalacha, Bubisa, Turbi, Ngurunit, Illaut, South Horr, Lontolio, Loyangalani, Logologo, and Karare.

[24] The TLUs help standardize the quantification of the different livestock types. Under resource driven grazing conditions, the average feed intake among species is quite similar, about 1.25 times the maintenance requirements (1 for maintenance, and 0.25 for production; i.e., growth, reproduction, milk). Therefore, metabolic weight is considered the best unit for aggregating animals from different species, whether for the total amount of feed consumed, manure produced, or product produced. The standard used for one tropical livestock unit is one cow with a body weight of 250 kg (Heady, 1975), so that 1 TLU = 1 head of cattle, 0.7 of a camel, or 10 sheep or goats.

to shocks such as droughts. Not only is MUAC easily collected, but several studies show it to be a better predictor of child mortality than the weight-height (W/H) measure (Alam et al., 1989; Vella et al., 1994). We adjust the MUAC for child age and sex by converting World Health Organization (WHO) growth chart values to an MUAC *z*-score, shown to be a better indicator of wasting than a fixed cutoff value (WHO, 2009). We also restrict the data by excluding all children with a MUAC *z*-score above 6 or below -6, which results in the exclusion of two cases considered measurement errors.

3.4 Economic activities

The sampled households predominantly comprise pastoralists whose main economic activity is tending livestock, which accounts for 70 percent of the households' overall income. Nevertheless, as Table 17 shows, between 2009 and 2013, the households experience a certain increase in salaried, business, and casual income, which could imply household diversification of income sources away from livestock. In fact, salaried income ranks highest among non-livestock income types, followed by business income and casual labor, which includes temporary off-farm jobs, farm labor, and herding. Cash and food aid is also common across the sampled households, offered mainly through the government or non-governmental organizations (NGOs) that provide rationed cereals and food supplements for young children, primarily during drought years. On the other hand, net cash and in-kind transfers, which include remittances and clothes or other assistance from relatives, neighbors, and friends, vary little across the study period. Only a few households (less than 5 percent) are engaged in crop farming.

Table 17 Percentage income share by income sources

Income source	2009	2010	2011	2012	2013
Livestock	72.7	77.7	72.3	64.7	71.9
Salaried income	12.2	4.9	11	14.1	11.8
Business	7.6	10.5	6.6	10.9	7.7
Casual labor	2.6	0.8	2.7	4.4	4.7
Cash aid	0.9	2.3	1.4	1.5	0.7
Food aid	1.6	1	4.3	1.2	0.4
Net transfers	1.2	0.8	0.4	1.4	1
Crop income	0.9	2.1	0.8	1.5	1.6

Note: Means are based on annual data for 924 households.

As regards income share by region (Table 18), Central households show a more diversified income portfolio than those in other regions, with much higher rankings for salary, business, and casual income. This difference could result from this region's greater development and better roads and communication infrastructure, which facilitates the adoption of non-livestock income activities. On the other hand, the region also supports crop farming better than the other regions.

Table 18 Percentage income share by Region

Income source	Central	Maikona	Loiyangalani	Laisamis
Livestock	50.5	78.7	72.4	75.3
Salary income	7.8	3.8	5.7	4.1
Business	13.2	4.1	10.7	10.1
Casual labor	11.1	4.5	4.6	2.7
Cash aid	5.1	5.1	1.4	1.9
Food aid	3.8	2.7	2.1	1.7
Net transfers	2.9	0.7	1.7	2.6
Crop income	4.4	0.3	1.0	1.2

Note: Means based on annual data for 924 households.

Overall, despite increased livelihood diversification among pastoralists in the study area, diversification is usually practiced by livestock-poor households as a survival strategy. Such households tend to rely more on cash transfers and food aid than households with more livestock (Mburu et al., 2016).

3.5 Descriptive information

From this section onward, the unit of analysis is the child; specifically, children between the ages of zero and five within the 2009–2013 observation period. Because the IBLI only collected MUAC measures up until the age of five, we follow all children until they exceed the age range or drop out of the survey, which leaves us with an unbalanced panel of 1,506 maximum individual children over the observation period.

3.5.1 Summary statistics and regional variation

The descriptive statistics for both the whole sample and each of the four regions over the entire survey period are given in Table 19, which shows average MUAC *z*-score of less than -1 *SD*, with the situation in Loiyangalani and Laisamis being worse than in the Central or Maikona regions. The average proportion of malnourished children is approximately 18 percent but varies between 13 and 22 percent among the regions. As regards NDVI *z*-scores, the average indicates that overall, the weather conditions are worse than the 2000–2009 average, with an overall -0.31 *SD* lower greenness score. Although the Central and Maikona regions seem more developed, with more children living in households that own a phone or have access to sanitation, the share of families receiving public support is also higher in Central than in other regions, perhaps because its better infrastructure facilitates access. Central and Maikona also have fewer cases of children suffering from chronic diseases and show slightly lower values in the household dependency ratio, which is calculated by dividing the number of individuals under 15 plus the number of individuals over 64 by the number of individuals aged between 15 and 64.

Regarding income and wealth, we observe little differences between the regions and the average child in our sample lives in a family with 14 TLUs and an annual income of 138,600 Kenyan Shilling (Ksh). In addition to the level of income, diversification plays an important role in coping with the risk of drought. Hence, we follow the literature (Liao et al., 2015) and calculate two different diversification indices. To measure the diversity of livestock, we use the

Shannon-Weiner (or Entropy) Diversity Index, which ranges between 0 (no diversity) to 1 (high diversity) and distinguishes between camels, cattle, and goats and sheep. Based on livestock, business, salaried, cash aid, net transfers, we use the Inverse Herfindahl Index as a measure of income diversification wherein a single income source corresponds to an index value of 1, with increasing values for higher diversification. Although both indices are related, the Inverse Herfindahl Index places more emphasis on the number of sources than the magnitude for the respective income stream (see, Ersado, 2006 for details). Families in the Central region show a more diversified income stream, which may reflect the availability of alternative income opportunities.

Table 19 Descriptive statistics: child sample

	Full sample	Region			
Variables		Central	Maikona	Loiyangalani	Laisamis
MUAC *z*-score	-1.04	-0.91	-0.93	-1.20	-1.17
Malnourished (=MUAC *z*-score < -2)[a]	17.8	15.8	12.7	21.6	22.3
NDVI *z*-score (long dry season average)	-0.31	-0.35	-0.28	-0.26	-0.36
Number of people in household	6.47	6.57	6.03	6.65	6.69
Dependency ratio in household	1.62	1.48	1.47	1.75	1.87
Household head is male[a]	68.3	66.3	86.0	46.2	77.4
Age of household head in years	42.36	43.66	44.92	38.55	42.35
Education of household head in years	1.03	1.26	0.95	0.89	1.01
Household owns a phone[a]	41.2	56.5	44.2	36.4	23.4
Household has access to a toilet[a]	22.8	31.0	18.8	22.7	17.3
Child is male [a]	52.9	51.7	53.6	52.5	54.0
Age of the child in months	32.67	33.54	31.75	31.90	33.77
Child suffers from a chronic disease[a]	23.0	21.8	10.3	32.4	28.8
Household receives food aid [a]	14.1	18.7	13.9	13.6	8.8
Child receive supplemental feeding[a]	24.3	26.0	28.3	21.3	20.9
Number of TLUs	14.07	11.88	17.09	15.29	11.37
Herd diversity index[b]	0.37	0.33	0.41	0.32	0.43
Annual household income without aid (in 1,000 Ksh)	138.6	115.3	144.5	162.7	129.5
Covered by livestock insurance[a]	13.4	15.0	14.6	8.9	16.1
Income diversity index[c]	1.55	1.99	1.34	1.49	1.31
# of observations	3,302	882	872	889	659

[a]Measured in percentages.
[b]Measured as the Shannon-Weiner Diversity Index.
[c]Measured as the Inverse Herfindahl Index
Note: Values are based on the unweighted child means of the regression sample.

The histogram in Fig. 11 also shows that the MUAC *z*-scores closely follow a normal distribution[25]. The one SD shift in mean, however, indicates that the average child in Marsabit has a lower MUAC than approximately 80 percent of the reference population.

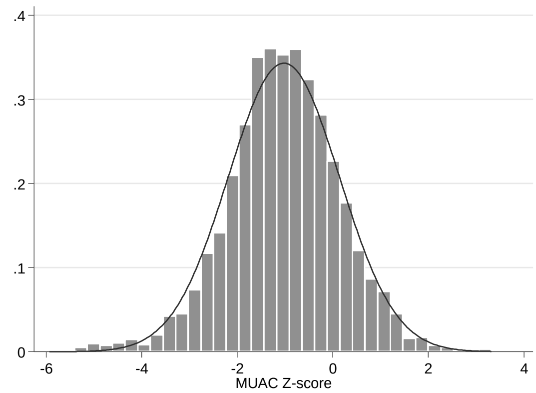

Figure 11 Distribution of MUAC z-scores

3.5.2 Longitudinal variation and food aid

Table 20 lists the descriptive statistics for our panel data, broken out by survey year. Here, the severity of the two major drought years suffered by the district in 2009 and 2011 is reflected by the low NDVI *z*-scores for the respective years: both averages for the long dry season are nearly one *SD* lower than the long term average. Additionally, as indicated by a MUAC *z*-score below -2 *SD*, the share of malnourished children is highest in the two drought years. The table also shows cell phone ownership and its expansion over time. Whereas in 2009, less than a third of the households owned a phone, in 2013, every second household does so.

[25] We also compute the distribution of height-for-age (HAZ), weight-for-age (WAZ), and weight-for-height (WHZ) *z*-scores (see appendix 6)Although only four waves include these measures, the WAZ that also measures short term wasting shows a distribution similar to that of the MUAC *z*-scores.

Table 20 Descriptive statistics: over time

Variables	2009	2010	2011	2012	2013
MUAC *z*-score	-1.10	-1.10	-1.24	-0.82	-0.95
Malnourished (=MUAC *z*-score < -2)[a]	20.6	18.9	21.9	13.1	14.1
NDVI *z*-score (long dry season average)	-0.95	-0.13	-0.90	0.18	0.39
Number of people in household	6.15	6.23	6.02	6.91	7.15
Dependency ratio in household	1.67	1.74	1.43	1.61	1.65
Household head is male[a]	67.8	67.6	67.0	68.8	70.8
Age of household head in years	42.4	41.6	42.0	42.5	43.3
Education of household head in years	1.30	1.21	0.85	0.93	0.77
Household owns a phone[a]	30.3	34.8	39.5	50.2	53.8
Household has access to a toilet[a]	21.3	21.2	22.3	25.8	23.6
Child is male[a]	53.5	54.1	52.7	52.3	51.6
Age of the child in months	31.62	33.48	32.94	33.81	31.45
Child suffers from a chronic disease[a]	27.1	22.6	20.8	17.2	27.6
Household receives food aid[a]	13.5	7.9	31.2	10.6	6.9
Child receive supplemental feeding[a]	36.9	25.0	41.4	10.2	4.9
Number of TLUs	16.93	16.16	11.63	11.97	13.21
Herd diversity index[b]	0.37	0.34	0.39	0.37	0.38
Annual household income without aid (in 1,000 Ksh)	121.3	87.7	138.9	160.4	193.1
Covered by livestock insurance[a]	0.0	25.6	27.4	8.1	7.5
Income diversity index[c]	1.84	1.23	1.55	1.64	1.44
# of observations	742	660	645	679	576

[a]Measured in percentages.
[b]Measured as the Shannon-Weiner (or Entropy) Diversity Index.
[c]Measured as the Inverse Herfindahl Index.
Notes: Values are based on the unweighted child means of the regression sample.

As evident from Table 20, the number of households receiving food support increases in drought years, indicating that both the government and NGOs react to weather conditions in the study area. The institutional drought coping mechanisms are mainly cash transfer, food for work from both government and non-government agencies, and food aid, mainly in the form of cereals and oils. Following drought periods, livestock restocking programs furnish households with a female cow to compensate for lost livestock, while supplementary feeding programs target pregnant and lactating mothers and provide malnourished children under five with nutritional supplements like peanuts, Plumpy'Nut[26], and soybeans. The children that are entitled to supplements are identified through regular MUAC assessments, which consider MUACs under 11.5 cm (over 11.5 cm but less than 12.5 cm) to indicate severe (moderate) malnutrition

[26] Plumpy'Nut is a peanut-based paste in a plastic wrapper used to treat malnutrition.

(Government of Kenya, 2014b). The malnourished child continues receiving supplements until the required MUAC measurement has been attained.

The correlation between child health and local weather conditions is illustrated in Figure 12, which shows a similar overall pattern for both MUAC and NDVI *z*-scores, with low points in the drought years of 2009 and 2011. This positive correlation between MUAC *z*-score and NDVI *z*-score implies that during periods of good forage, children on average enjoy better health.

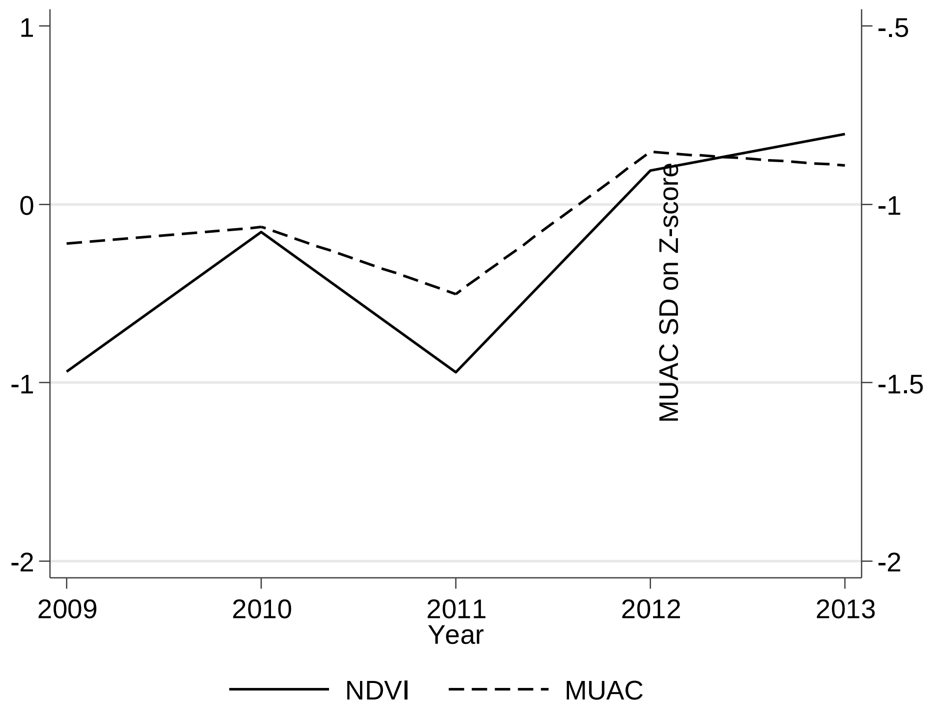

Figure 12 MUAC and NDVI z-scores

To highlight the negative correlation between the NDVI *z*-score and food support programs, Figure 13 plots the share of children who do *not* benefit from a supplemental feeding program or live in a household that does *not* receive food aid. Here, a higher NDVI *z*-score indicates better weather conditions, which translate into a lower need for food support. As expected, the proportion of children without food support is highest in non-drought years; however, lower

NDVI *z*-scores and a lower proportion of children without food support are also recorded in the drought years of 2009 and 2011. This same trend replicates across the different regions studied.

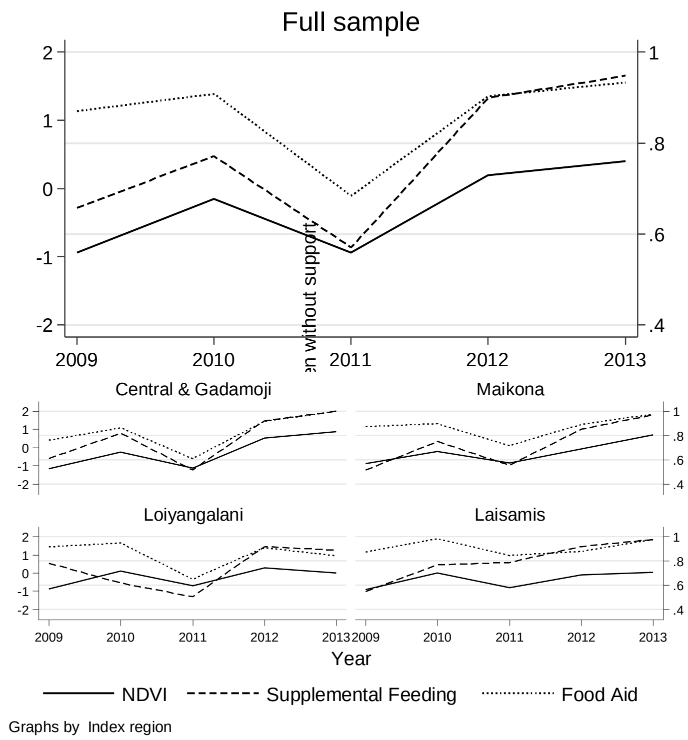

Figure 13 NDVI z-score and food support

3.6 Methodology

Given our interest in drought's effect on child health, we isolate the effect of NDVI on MUAC using a multivariate model that controls for possible confounding factors (cf. Grace et al., 2015). Because the NDVI *z*-score is a strongly exogenous variable, we expect its coefficient to be free from endogeneity bias, allowing a close-to-causal interpretation of the relation being studied. Nevertheless, correct model specification is crucial in this context because many potential covariates (e.g., size of livestock) represent causal pathways through which drought could affect child nutritional status. Any conditioning on assets and income, however, could be considered over controlling that reduces the true effects of drought (Schisterman et al., 2009). Likewise, malnutrition could be attributed to a lack of milk and high livestock mortality, which are primary pathways to understanding how weather conditions influence the local population. Hence, rather than including these variables in our main regression, we analyze them separately.

To test the sensitivity of the NDVI coefficient through the addition of more covariates, we apply a stepwise structure that gradually integrates an increasing number of controls. In its most extensive form, the model can be expressed as follows:

$$y_{ijrt} = \beta_o + \beta_1 n_{rt} + \beta_2 C_{ijrt} + \beta_3 H_{jrt} + \beta_4 z_t + \beta_5 g_r + \varepsilon_{ijrt} \quad (1)$$

Here, the indices represent child *i*, who lives in household *j*[27], located in region *r*, and observed in time *t*. The dependent variable y_{ijrt}, is child nutritional status as measured by the MUAC *z*-score[28]. Drought is again measured as the average NDVI *z*-score n_{rt} in the long dry season of the respective region. This latter, however, although it accounts for regional variation, does not control for other interregional differences that may be correlated with child health. We therefore add in controls for both child and household characteristics. The child characteristics C_{ijrt} are child age, child gender, and a dummy for chronic illness; the household characteristics H_{jrt}, are family size and structure; gender, age, and education of household head; ownership of a phone[29]; and access to a toilet. We also include a time dummy z_t and regional dummy g_r to account for broad interregional differences[30] and general development over time. ε_{ijrt} indicates the error term, which we cluster on a regional and yearly level to account for the aggregated nature of the NDVI data (see Moulton, 1990)[31].

We then extend this basic model to isolate the possible pathways through which drought may affect child health (see Brown et al., 2014). To do so, we use three groups of variables to

[27] We expect little bias for variables measured on the household level, because none of the household clusters exceeds 5 percent of the total sample size (Rogers, 1993).

[28] The data set also contains information on HAZ, WAZ, and WHZ; however, only for the first four waves because only MUAC was collected throughout the survey period.

[29] Pastoralist will rarely sell their phone in times of scarcity in order to buy food, as they are usually more a development and connectedness measure than an asset (Donner, 2008).

[30] Even though the original survey sampling procedure involved randomization on the sublocation level, we find few differences when compared to including sublocation fixed effects and when standard errors are clustered on this lower level. We therefore do not incorporate these checks into the main analysis, although the corresponding results are available upon request.

[31] To control for the risk that the standard cluster-robust variance estimator can perform poorly when the number of clusters is small (Cameron et al., 2008), we apply a wild cluster bootstrap-t procedure, whose results (available upon request) remain quantitatively similar.

measure the mediating effect of livestock, income, and food support on the relationship between NDVI and the MUAC of children.

Although our data provide a rich set of covariates, some important characteristics that affect the drought-child health relation may still be unobservable. To account for this possibility, we exploit the longitudinal nature of the data and apply a fixed-effects model. To derive the household fixed-effects model while removing all individual time-invariant unobserved heterogeneity, we time-demean equation 1 in a within transformation that also removes all time-invariant observable characteristics such as child gender or regional dummies (unless the child moved within the survey period).

Although our linear models estimate an average coefficient for the whole distribution of children, we are particularly interested in the most vulnerable located at the left tail of the MUAC distribution. Because children with less than 2 *SD* below the mean are generally considered malnourished (CDC and WFP, 2005), we dichotomize our main dependent variable as follows: if a child is above -2 *SD* of the *z*-score, we recode the MUAC *z*-score to a 0, meaning that 1 indicates malnourishment. The logit model, which mimics the specification in regression 1, estimates the probability of a child being below the threshold and thus malnourished.

Dichotomizing the dependent variable at a certain cutoff, however, leads to information loss, so we also apply a quantile regression at the 0.25, 0.5, and 0.75 quantiles to assess whether the drought effect and/or its relation with other covariates differs along the MUAC *z*-score distribution.

3.7. Results and discussion

In the linear multivariate analysis reported in Table 21, the pooled ordinary least squares (OLS) models (columns 1–3) also include time and regional dummies, raising the possibility of a multicollinearity problem between time, region, and the NDVI *z*-score, measured as cumulative values for each region in each year[32]. Unfortunately, the data limitation of only four regions and five survey years limits the potential for variation between these variables. Nevertheless, because a variance inflation factor test reveals only values below the critical threshold of 10, we include the NDVI *z*-score in our linear specification.

The regression model has three steps for all estimations, with subsequent introduction of a richer set of covariates designed to test the NDVI *z*-score coefficient's sensitivity to the control variables. Generally, we find a significant and positive effect of the NDVI *z*-score on the MUAC *z*-scores of children under five: in the most parsimonious model (model 1), a change of 1 *SD* in the NDVI *z*-score produces a 0.52 change in the *SD* of the MUAC *z*-scores. This comparably strong effect remains constant despite the inclusion of additional covariates.

In column 2, which adds in the child characteristics, both child gender and child age show a significantly negative correlation with the dependent variable. The effect of NDVI is slightly larger than in column 1, suggesting that child characteristics differ slightly between regions, although in general, boys seem to be in slightly worse health than girls. This finding, also reported in previous studies (Kigutha et al., 1995; Grace et al., 2012) might be attributable to girls spending more time with their mothers in the kitchen, giving them preferential access to the limited food. Sellen (2000), however, finds little evidence for gender differences in food access among pastoralists in the north of Tanzania. On the other hand, our finding that older children tend to be worse off confirms a previous report by Chavez et al. (2000) that the risk of undernutrition increases with child age. This increase could be related to older children's introduction to complementary feeding and weaning from nutritionally rich breast milk (Asenso-Okyere et al., 1997). Older children are also increasingly involved in household labor, such as animal herding and water collection (Sellen, 2000).

[32] We use this measure because the regions are clustered by climate-related characteristics, meaning that lower level aggregation would provide little additional variation. Likewise, pastoralists are known to travel large distances in times of water shortage, so a narrow aggregation would be no better proxy for local conditions.

With the addition of further household controls in column 3, the NDVI *z*-score lowers slightly, and we observe a significant relation between phone ownership and child nutritional status. This relation may reflect the fact that phone ownership helps the households obtain information about livestock prices on the market, new grazing areas, receive remittances and/or food aid programs, which can ultimately improve the family members' nutritional status. We also find an association between improved child health and the educational level of the household head (Desai and Alva, 1998), a frequent proxy for socioeconomic status, is a distinct predictor of better child health in more urban areas of Kenya (Abuya et al., 2012).

Columns 4-6 in Table 21 show the results of the fixed-effects regression, in which the main variable of interest, the NDVI *z*-score, is slightly smaller in magnitude than in the pooled OLS. Overall, however, the results appear generally robust and only vary slightly across the different specifications[33], suggesting that any bias from unobserved characteristics is minimal. Not only do the fixed-effect results support the negative relation between child age and health, they also show an association between lower child health and increasing household size. However, the other significant covariates in column 6 should be treated with caution because the majority of these variables remain unchanged over the survey period.

[33] As a further test of robustness, we run a regression based on the weighted regional-year averages (20 observations). The results are similar to the micro-level data, with an NDVI coefficient of 0.55 and a p-value below 0.05 when only time effects are controlled for.

Table 21 The effect of drought on child nutritional status

Dependent variable	MUAC *z*-score					
	Pooled OLS			Household Fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
NDVI *z*-score	0.523***	0.594***	0.475***	0.458***	0.517***	0.431***
	(0.130)	(0.121)	(0.124)	(0.121)	(0.110)	(0.108)
Child characteristics						
Male		-0.093**	-0.060			
		(0.035)	(0.038)			
Age in months		-0.018***	-0.018***		-0.034***	-0.032***
		(0.002)	(0.002)		(0.003)	(0.003)
Chronic disease		-0.013	0.006		0.057	0.087
		(0.058)	(0.054)		(0.055)	(0.054)
Household characteristics						
Size			-0.012			-0.092***
			(0.011)			(0.028)
Dependency ratio			-0.025			-0.016
			(0.026)			(0.038)
Head is male			0.045			0.717***
			(0.083)			(0.222)
Age of head			-0.002			-0.018***
			(0.002)			(0.004)
Education of head in years			0.027***			0.018
			(0.009)			(0.033)
Phone ownership			0.274***			0.199**
			(0.059)			(0.083)
Access to toilet			0.017			-0.269**
			(0.063)			(0.112)
Constant	-0.444***	0.269*	0.148	-0.306**	0.090	0.779**
	(0.145)	(0.144)	(0.229)	(0.142)	(0.153)	(0.308)
N	3589	3581	3309	3589	3581	3309
Adj. R2	0.04	0.11	0.13	0.05	0.08	0.09

Notes: All regressions include dummies for observation year and region. The latter is also included in the fixed-effects models to account for children moving between regions during the study period. Robust standard errors clustered by region and year are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 22 presents the results for the pooled OLS (columns 1 to 4) and fixed-effects estimations (columns 5 to 8) once the channel variables are added into the regressions. In column 1, which includes the number of TLUs (representing the pastoralists' main asset) and a herd diversification index, we find a rather surprising negative correlation between TLUs and child health. The point estimates for this correlation, however, are small and only significant at a 10 percent level, and the coefficient is mainly driven by a few outliers with a very large number of TLUs, whose removal wipes out the relation[34]. Column 2 then incorporates

[34] Excluding 11 child-year observations with TLU numbers over 200.

cumulative household income without food aid, the ownership of livestock insurance, and the Inverse Herfindahl Index as an indicator of income diversification. These variables exhibit no relation with child health, which is in line with some previous findings and might stem from the common practice of pastoral households sharing milk (Fratkin, 2005).

Column 3 adds in the different types of food support provided in supplemental feeding, which shows a significant but negative relation with child health. This rather unintuitive negative sign, however, should be interpreted in light of a possible reverse causality; that is, children in poor health may be more likely to receive food aid. Neither is reverse causality the only challenge in measuring the mediating effect of food aid on child health. During the 2011 drought, for example, a substantial delay was evident between the first drought indications and food availability in the area (Oxfam, 2012). Even beyond slow decision-making processes, poor infrastructure can restrict access and cause delays in the delivery of emergency food aid, as can safety and security concerns coupled with poor stakeholder coordination in identifying vulnerable households. Such delays can lead to severe malnutrition or even death, with affected children unable to recover even after receiving the food. Moreover, given the limitations of the yearly health data, we cannot rule out a delayed drought response mediating more of the NDVI effect at a later point in time. Integrating all channel variables into the regression (column 4) leads to a slightly reduced effect size of the NDVI *z*-score, our main variable of interest. Even though, not captured by the data, additional coping strategies might mitigate the effect of drought. For instance, when households ration food, children often eat first. Additional coping strategies include livestock migration to less dry pasture and sending children to other relatives.[35] The household fixed-effects results closely mimic the pooled OLS estimations: the NDVI *z*-score consistently falls between 0.4 and 0.5.

[35] This information is based on focus groups discussions conducted by the authors in November 2014 in the study area.

Table 22 Effect of channeling variables on child health

	Pooled OLS				Household Fixed effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NDVI *z*-score	0.474***	0.472***	0.431***	0.426***	0.433***	0.425***	0.412***	0.407***
	(0.125)	(0.124)	(0.115)	(0.116)	(0.106)	(0.109)	(0.105)	(0.104)
Number of TLUs	-0.002*			-0.003*	0.001			0.001
	(0.001)			(0.002)	(0.001)			(0.001)
Herd diversity index[a]	0.139			0.140	0.087			0.091
	(0.084)			(0.084)	(0.117)			(0.115)
Household income		-0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Household has insurance[b]		0.067		0.035		-0.026		-0.049
		(0.088)		(0.084)		(0.053)		(0.054)
Income diversity index[c]		-0.002		-0.002		-0.002		-0.003
		(0.002)		(0.002)		(0.002)		(0.003)
Child receives supplementary feeding			-0.326***	-0.322***			-0.264***	-0.264***
			(0.069)	(0.067)			(0.058)	(0.058)
Household receives food aid			-0.078	-0.084			0.052	0.046
			(0.058)	(0.057)			(0.049)	(0.050)
Constant	0.137	0.155	0.223	0.211	0.721**	0.766**	0.875***	0.806**
	(0.223)	(0.230)	(0.223)	(0.218)	(0.326)	(0.313)	(0.302)	(0.322)
Observations	3302	3309	3309	3302	3302	3309	3309	3302
Adj. R2	0.13	0.13	0.14	0.15	0.09	0.09	0.10	0.10

[a]Measured as the Shannon-Weiner (or Entropy) Diversity Index.

[b]Refers to index-based livestock insurance

[c]Measured as the Inverse Herfindahl Index.

Notes: All regressions include controls for child (age, gender, sickness) and household characteristics (size; dependency ratio; gender, age, and education of household head; phone and toilet ownership), plus dummies for observation year and region. The latter is also included in the fixed-effects models to account for some children moving between regions during the study period. Robust standard errors clustered by region and year are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 23 reports the results of our binary regressions,[36] whose interpretation we facilitate by calculating the average marginal effects for all coefficients. Columns 1 to 7 adopt the same specifications as the linear model. Again, the drought measure shows robust coefficients over all specifications, with a 1 *SD* increase in NDVI *z*-score associated with a 12 to 16 percent reduction in the average probability of malnourishment. For the covariates, the logit model generally supports the OLS results but with several noteworthy exceptions: First, gender differences are more robust than in the analysis of the whole distribution; boys are clearly more

[36] We also estimate a fixed-effects logit model (results available upon request) that generally supports the pooled estimations.

prone to being malnourished. Second, even when household composition is controlled for, children from larger households are more likely to be malnourished, a one person increase in family size is associated with 0.8 percent increased risk for the child. Third, the gender of the household head seems to matter in that we observe a positive and significant relation between male-headed households and child nutritional status. This relation, however, is weak and vanishes once all controls are added into the regression. Fourth, from households with a more diversified herd composition are better off. This finding suggests that owning different types of animals may improve the owners' ability to cope with weather shocks. Such heterogeneous livestock composition is in fact a common coping strategy among pastoralists in Kenya because it diversifies risk and allows more flexibility in harsh times (Opiyo et al., 2015). Finally, the livestock insurance seems to be an effective risk management tool, as it slightly reduces the probability of malnutrition among children.

Table 23 Effect of NDVI z-score on malnourishment

	Dependent variable: Dummy indicating 1 if the child is malnourished (=MUAC *z*-score < -2)						
	LOGIT (marginal effects)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NDVI *z*-score	-0.146***	-0.158***	-0.141***	-0.142***	-0.138***	-0.126***	-0.125***
	(0.041)	(0.041)	(0.049)	(0.048)	(0.048)	(0.046)	(0.044)
Child characteristics							
Male		0.036***	0.030***	0.029***	0.030***	0.030***	0.028***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age in months		0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Chronic disease		0.013	0.008	0.007	0.008	0.004	0.003
		(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)
Household characteristics							
Size			0.008**	0.008**	0.008**	0.007**	0.008**
			(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Dependency ratio			0.004	0.004	0.004	0.005	0.005
			(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Head is male			-0.032*	-0.028	-0.032*	-0.028	-0.026
			(0.018)	(0.017)	(0.017)	(0.018)	(0.017)
Age of head			0.000	0.000	0.000	0.000	0.000
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education of head in years			-0.004*	-0.004*	-0.005**	-0.004	-0.004
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Phone ownership			-0.065***	-0.067***	-0.065***	-0.068***	-0.069***
			(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Access to toilet			-0.000	-0.004	-0.001	-0.006	-0.011
			(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Channel variables							
Number of TLUs				0.000			0.000
				(0.000)			(0.000)
Herd diversity index[a]				-0.054*			-0.052*
				(0.030)			(0.029)
Household income (w/o aid)					0.000		0.000
					(0.000)		(0.000)
Household has insurance[b]					-0.058**		-0.048*
					(0.028)		(0.026)
Income diversity index[c]					0.000		0.000
					(0.001)		(0.001)
Child receives supp. Feeding						0.096***	0.093***
						(0.019)	(0.020)
Household receives food aid						0.020	0.022
						(0.022)	(0.023)
N	3589	3581	3309	3302	3309	3309	3302
Pseudo R^2	0.03	0.05	0.06	0.06	0.06	0.08	0.08

[a]Measured as the Shannon-Weiner (or Entropy) Diversity Index.

[b]Refers to index-based livestock insurance

[c]Measured as the Inverse Herfindahl Index.
Notes: This table reports the average marginal effects of the logit models. Insurance refers to index-based livestock insurance. All regressions include dummies for observation year and region. Robust standard errors clustered by region and year are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Finally, Table 24 reports the results of the quantile regressions, which are based on the main specification in Table 21, column 3. These outcomes, which are similar overall to previous findings, reveal the strongest NDVI *z*-score effect among the median and lowest in the top quartile. This observation might be explainable by stronger food program intervention among the most vulnerable, which would reduce the correlation's magnitude. In these estimations, boys again seem to be worse off but only in the lowest quantile, which echoes the results of the binary regressions. Here, however, a higher educational level only seems to make a contribution in the higher distribution.

Table 24 Quantile regression on the distribution of child MUAC z-scores

	Dependent variable: MUAC *z*-score		
	Quantiles		
	25th	50th	75th
NDVI *z*-score	0.432***	0.523***	0.370***
	(0.099)	(0.093)	(0.109)
Child characteristics			
Male	-0.145***	-0.066	0.028
	(0.046)	(0.045)	(0.050)
Age in months	-0.013***	-0.018***	-0.022***
	(0.001)	(0.001)	(0.002)
Chronic disease	0.027	0.082	-0.002
	(0.056)	(0.054)	(0.053)
Household characteristics			
Household size	-0.030***	-0.018	-0.019
	(0.012)	(0.011)	(0.013)
Dependency ratio	-0.030	0.005	-0.023
	(0.025)	(0.023)	(0.024)
Head is male	0.096*	0.043	0.002
	(0.057)	(0.060)	(0.058)
Age of head	-0.002	-0.003	-0.001
	(0.002)	(0.002)	(0.002)
Education of head in years	0.013	0.019**	0.035***
	(0.009)	(0.008)	(0.010)
Phone ownership	0.302***	0.295***	0.253***
	(0.058)	(0.048)	(0.056)
Access to toilet	0.026	0.015	0.082
	(0.055)	(0.062)	(0.066)
Constant	-0.676***	0.250*	0.978***
	(0.172)	(0.142)	(0.170)
N		3309	

Notes: All regressions include dummies for observation year and region. Robust standard errors bootstrapped with 1,000 replications clustered by year and region are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.8 Conclusions

In the hope of improving health among pastoralist children in Kenya's drought prone Marsabit district, this study investigates the prevalence of malnutrition among children under five in this area. The analysis reveals a clearly left-skewed distribution of MUAC *z*-scores (which proxy nutritional status) and identifies approximately 20 percent of the children studied as malnourished (MUAC *z*-score <-2 SD). These observations are particularly valuable given Northern Kenya's distinct characteristics of poor child health, low vegetation, and little education (Grace et al., 2014). In the Marsabit district, specifically, pastoralism is still the dominating lifestyle, which makes food availability particularly sensitive to weather conditions.

To improve understanding of the relation between child health and weather conditions, we combine IBLI household panel data and NDVI satellite data to estimate the effect of drought on child health. Throughout all our model specifications, NDVI has a robust effect on child MUAC, implying a strong link between drought and malnutrition in children under five. More specifically, a one point increase in NDVI *z*-score increases the MUAC z-score by approximately 0.5 *SD*. This drought effect is further supported by our analysis of the dichotomized dependent variable using a -2 *SD* cutoff as the child malnutrition indicator. These results reveal that a 1 *SD* increase in NDVI *z*-score leads to 12 to 16 percent decrease in the probability of children being malnourished.

Although several other studies document a link between drought and child health (see Stanke et al., 2013; Brown et al., 2014; Grace et al., 2015), the effects identified vary strongly and often depend on local conditions. In this study, we identify a relatively strong and robust effect for the NDVI measure, which nevertheless must be interpreted in light of clearly endogenous NGO and government efforts to reduce the impact of drought (e.g., the UN appeal for over 2 billion dollars to ease the effects of the 2011 drought in Eastern Africa; Oxfam, 2012). Because of the broad scale of the interventions that provide food aid when insufficient forage puts livestock at risk, we are unable to conduct a quasi-experimental analysis that clearly assesses the impact of either drought or food support. Nonetheless, the strong correlation we document between drought and child health does raise concerns about the effectiveness of these programs, although the weaker drought effect at the 25th quantile than at the median could reflect success in protecting the most vulnerable when weather conditions are severe.

Child health, however, is also impacted by local conditions and family characteristics, which leave older children worse off than younger siblings who are still being breastfed or receive better care. In the most vulnerable households, boys are worse off than girls. At the same time, male-headed households tend to have healthier children, while family size is negatively associated with child MUAC. As regards local coping strategies, despite some evidence that better child health may be linked to livestock herd diversification, we cannot fully identify all the channels through which it is affected by drought. Such identification is difficult because food insecurity is complex and the drought effect, in addition to channeling through reduced milk and meat production, may depend on additional determinates such as the market prices for food staples (Grace et al., 2014).

Nevertheless, this study highlights the considerable effect that drought still has on the health of young children in the area. More important, it implies that currently, neither food aid nor local coping strategies are fully mediating the negative effects of changing weather conditions. This failure warrants particular attention given the increased frequency and severity of droughts over the last 100 years (O'Leary and Palsson, 1990). If, as expected, climate change brings about increasingly extreme weather conditions, these will pose an even larger threat in the future (Stern, 2006). More effort is thus required to reduce the vulnerability of these children during periods of insufficient rainfall.

In the light of our results, food aid as an emergency response may be deemed insufficient. For example, in 2011, despite early warnings (e.g., from FEWSNET), the aid provided was criticized as "too little and too late" (Oxfam, 2012). Hence, food safety programs and other response mechanisms need timelier and better targeted interventions. As demonstrated here, remote satellite data can help to monitor conditions in rural areas; however, warnings must translate into actions. Following interventions, these data could also be used to evaluate intervention efficacy and thereby improve the efficiency of humanitarian assistance.

Nevertheless, even though improved interventions strategies would certainly be of benefit, food aid can only supplement local efforts to reduce household dependency on weather conditions. For pastoralists, assets, income, and home production are tightly linked to their livestock, meaning that drought endangers all these factors simultaneously, which implies that a more diversified economy could improve resilience to weather changes. First indications of this process are in fact already observable in the study as households increasingly shift their efforts from pure pastoralism to non-livestock income activities. This transition could be facilitated by policies that promote income diversification and programs that promote capacity building and support non-weather related economic activities through increased access to credit and improved infrastructure (Opiyo et al., 2015). Dependency on local weather conditions could also be reduced among crop farmers by advancing the technology of water harvesting in small scale irrigation to permit crop expansion.

Chapter Four: Effects of Livestock Herd Migration on Child Schooling in Marsabit District, Kenya

Abstract

To throw light on the challenge of providing education to pastoral households in the context of social and economic change, this study investigates the effects of herd migration on child schooling in Northern Kenya. Specifically, the analysis uses both household panel data and community-level focus group data to identify the barriers to schooling, which include an insufficient number of schools, nomadism, and communal conflicts. The results also reveal that, once other factors are controlled for, herd migration has a significantly negative effect on school attendance, about a 26% probability of failure to attend among the children of livestock migrating households. Child schooling is also negatively affected by illness of the household head. The child's age and mother's literacy, in contrast, have a positive impact on child school attendance, but with girls more likely to attend than boys, probably because of higher opportunity costs. That is, attending school takes boys away from activities like herding, which have greater economic value than the nonmonetizable household duties performed by girls.

Key words: education, children, pastoralists, drought, livestock

4.0 Introduction

Because investment in childhood education is recognized as one of the basic requirements for economic development, the United Nations' sustainable development goals include inclusive and quality education for all by 2030 (United Nations 2015). As of 2015, however, even though primary school enrollment in developing regions had risen from 83% in 2000 to 91%, around 57 million children of primary school age were still not in school (United Nations 2015). Yet improved education levels in a population translate into better skills and improved access to job opportunities, which in turn lead to improved hygiene and household welfare. For example, Little et al. (2009) show that having a family member with secondary and post secondary education and stable employment in the formal sector can improve welfare and help households cope with natural disasters. The provision of such formal education to pastoral communities that usually migrate in search of water and grazing pasture, however, is a major challenge, with an estimated global total of nomadic out-of-school children of around 21.8 million (Carr-Hill 2012).

In these communities' areas of residence, the accessibility challenge posed by underinvestment in schools (Dyer 2013) is coupled with insecurity, low population density, and harsh physical conditions that make it harder to attract both learners and an adequate numbers of teachers (McCaffery et al. 2006). Pastoralists are thus among several groups identified as having been discriminated against in educational access, meaning that if the fast approaching sustainable development goal of universal education is to be met, efforts must focus on their inclusion in educational policies (UNESCO 2010). Such inclusion requires an understanding of pastoralism[37] as a viable means of livelihood and a shift away from traditional view of education as a tool to transform pastoralists into settled livestock keepers or wage laborers (Dyer 2012; Aikman 2011). In the African drylands specifically, pastoralism continues to be a major economic driver because productivity relies greatly on the herd mobility that enables optimal use of grazing pastures across the rangeland. This mobility, however, has critical implications for the provision of education (Krätli and Dyer 2009).

In 2003, the Government of Kenya introduced universal free primary education that enabled children to attend school without paying fees and other levies. At that time, the support per child was pegged at 1,020 Kenyan shillings to support instructional materials, co-curricular activities, and wages for nonteaching staff. This change in education policy reactivated the then stagnant education system and resulted new primary school enrollment of over one million children. Between 2002 and 2006, the total number of primary school children increased by 9.7% from 185,900 to 210,528, and public primary school enrollment increased by 23.4% from

[37] Pastoralism refers to the practice of herding livestock – mainly cattle, sheep, goats, and camels – as the primary economic activity.

5.87 million to 7.26 million students (IEA 2008). The government effort to enhance educational access in the country has since been reflected in increasing budget allocations to the education sector, which received 273.3 billion Kenyan shillings (27.3% of the total budget) in the 2013/2014 fiscal year. Part of this allocation, the government disbursed 32 billion Kenyan shillings for free milk program as well as school feeding programs (Government of Kenya 2014).

Despite such efforts, however, schools in Kenya's arid and semi-arid districts[38] have recorded lower enrollment and attendance rates than in the rest of the country (Ruto et al. 2010). These districts, being the most geographically marginalized, have long been neglected in terms of development, with only 32.3% of children over six attending school in 2008 compared to the national average of 76.8% (KNBS 2008). Another study by ADESO (2015) further indicates that girls' transition rate from primary to secondary school in Marsabit district is only 28% compared to a national average of 72%, while the completion rate is 42% against a national average of 74%. Even the abolition of school fees has failed to catalyze school enrollments in these areas relative to other regions in the country (Ruto et al. 2010).

These areas, however, account for about 20% of the country's population, with the nomadic pastoralism that is the main source of livelihood contributing about 70% of the nation's total livestock production (Government of Kenya 2008). The households that engage in this livelihood, however, cope in the best way possible with a variety of challenges, including climate variability, droughts, and conflicts. In fact, it is the persistent droughts in the area over decades (Chantarat et al. 2012) that have made mobility (herd migration) a key strategy for coping with the harsh climatic conditions. This mobility involves seasonal migration from place to place in search of the best available pastures and watering points across the rangelands (WISP 2007). During these migrations, the children are sometimes expected to provide herding labor,

[38] These districts include Turkana, Samburu, Marsabit, Isiolo, Moyale, Mandera, Wajir, Garissa, Ijara, and Tana River.

or stay at home which hinders their access to formal schooling. With young children going to school, there is redistribution of household tasks including herding being undertaken by parents. This may not be harmful but could make the households more vulnerable to drought risk. According to Birch et al. (2010), too many pastoralist households are still unable to reconcile a desire to educate their children with the loss of their participation in family labor. In this context, therefore, it is important to understand the extent of formal schooling and the challenges faced by school children in these marginal areas.

This study has three primary objectives: to identify levels of school enrollment, especially gender differences between boys and girls; to estimate the effect of herd migration on school attendance; and to understand community perceptions and challenges to formal education. To achieve these goals, the analysis draws on both household survey panel data and data from focus group discussions (FGDs) conducted in the study area. To the best of our knowledge, no other comprehensive studies currently exist on the relation between herd migration and child schooling in the Marsabit district.

4.1 Previous Literature

Although a number of studies examine the relation between formal education and pastoralism, the findings are mixed. Some studies provide evidence of uncertainty among pastoralists who on the one hand see schooling as a threat to their social institutions and thus to their pastoral livelihood and on the other, as an adaptation strategy that could provide their family with an alternative means of livelihood (Government of Kenya 2010). Researchers also point to the problem of historical biases. Idris (2011), for instance, comments that pastoralism has long been viewed as an evolutionary stage between hunting and gathering and modern sedentary life and thus likely at some time to “die a natural death.” In this case, education and pastoralism are seen as mutually exclusive, with education only an exit strategy out of pastoralism and an educated pastoralist a mere anomaly. Pragmatically, however, it is true that the absence of children from a pastoral household limits the labor availability that is crucial to successful mobility and constitutes a critical risk management strategy for pastoralists (Fratkin 1986).

Other challenges to schooling among pastoral communities are outlined by Krätli and Dyer (2009) and Dyer (2012), who argue that the current school education curriculum is designed for children to learn in some permanent location at a particular time. It thus ignores the mobile nature of the pastoral population and the need for child labor in certain household activities such as herding. Such a curriculum ultimately conflicts with household mobility patterns, creating a disconnect that partly explains low school enrollment and completion in the pastoral districts. This argument is supported by Sifuna (2005) and Ruto et al. (2010), who show that the school curriculum design is not responsive to the needs of pastoral communities in Kenya. Specifically, these authors argue that since colonial times, pastoral areas have been marginalized in terms of education facilities and have been little affected by attempts to address imbalances, whether school lunch programs, boarding school construction, or school fee waivers. They thus suggest that education provision should better address the diverse lifestyles of pastoral communities by including a mix of both fixed and mobile schools. Krätli and Dyer (2001) further point out that formal education among some Turkana and Karamoja communities in Kenya undermines certain social institutions by displacing local knowledge and social relationships that are critical for a pastoral livelihood. Not surprisingly, given the viability of pastoralism for sustenance in the drylands, when formal education is presented as an exit strategy from an allegedly backward evolutionary stage, the pastoralists resist it in order to preserve their social institutions.

Recently, however, many pastoralists have begun expressing a renewed interest in and a more positive attitude toward formal education. According to focus groups conducted in Kenya by Idris (2011), for example, in the face of changing climatic conditions and the resulting huge losses in livestock, many pastoralists have begun to appreciate the value of education as a potential provider of alternative livelihoods. The main concern for these group participants was the disruption of their pastoral economy by the labor loss from absent children. To balance these aspects, they send some children to school but keep others at home to provide labor. This compromise echoes Dyer's (2012) observation that pastoralism and education are not intrinsically incompatible, but combining the two requires an educational setup that accommodates learners who, while acquiring a formal education, are also expected to become successful pastoralists capable of managing herd migration and supporting social and informational pastoral networks.

Other studies focus on identifying the determinants of child schooling in different regions. For instance, Hyder et al. (2015) show that negative economic shocks in rural households in Malawi are associated with fairly high rates of class repetition, especially among older children with a negative grade attainment gap. In this study, child enrollment is significantly positively affected by the education level and wealth status of the household head but not by child gender, although school grade attainment is higher for girls than for boys even when their enrollment numbers are no different. This finding implies that boys repeat classes more often than girls, a widespread phenomenon in developing countries (Grant and Behrman 2010). A similar study for Ethiopia by Mani et al. (2013) indicates that school enrollment is positively, but not significantly, associated with land but negatively and significantly associated with the interaction between land and rainfall. It also finds a positive relation between child enrollment and parental schooling, whose interaction with child gender produces positive, albeit statistically insignificant, coefficients. Specifically, a mother's schooling has a marginally higher impact on a girl's enrollment while a father's schooling has more effect on a boy's enrollment. In terms of school dropout rates, Glick et al. (2014) find that in their Madagascan sample (n =28,264 child-year observations) 13% of the children had dropped out of school, with only a 1% share of children under 10 but a 39% share of those over 17. They also demonstrate that both health and economic shocks impact the probability of dropping out, in particular, the death or sickness of the father or mother. On the other hand, income shocks (lower or higher incomes) seem to have no effect on school attendance, although lack of employment for the household head and loss of assets do have a lagged positive effect. Dropping out is negatively impacted by the presence of a nutrition program in primary school, which also leads to earlier school entry.

In sum, the literature underscores the uniqueness of education provision to pastoral communities given the potential tradeoff between formal education, which reduces the internal labor pool, and social institutions that support a lifestyle well adapted to the environment and provide these communities with local knowledge through informal learning. Hence, whereas free primary education is a noble idea, the pastoral way of life is critical in advancing the livelihoods of these communities. Yet knowledge on how livestock migration and related factors affect school attendance among pastoral children is sparse, a deficit that this study aims to remedy while also highlighting the strategies used by these communities to overcome barriers to formal schooling.

4.2 Study Area and Data

4.2.1 Study area

Marsabit district is characterized by an arid or semi-arid climate (rainfall of up to 200 mm/year in the lowlands and 800mm/year in the highlands), drought, poor infrastructure, remote settlements, low market access, and low population density (about 4 inhabitants per km^2). This area, which covers about 12% of the national territory, is home to about 0.75% of the Kenyan population and encompasses several ethnicities – including Samburu, Rendille, Boran, Gabra, and Somali – each with distinct languages, cultures, and customs. These pastoral communities live in seminomadic settlements in which livestock, the main source of livelihood, is moved across vast distances in search of grazing pasture, especially during the dry season. Largely dependent on milk from livestock (mainly camels or cattle) for home consumption, these communities also trade or sell animals (primarily goats and sheep) to purchase food and other commodities (Fratkin et al. 2005).

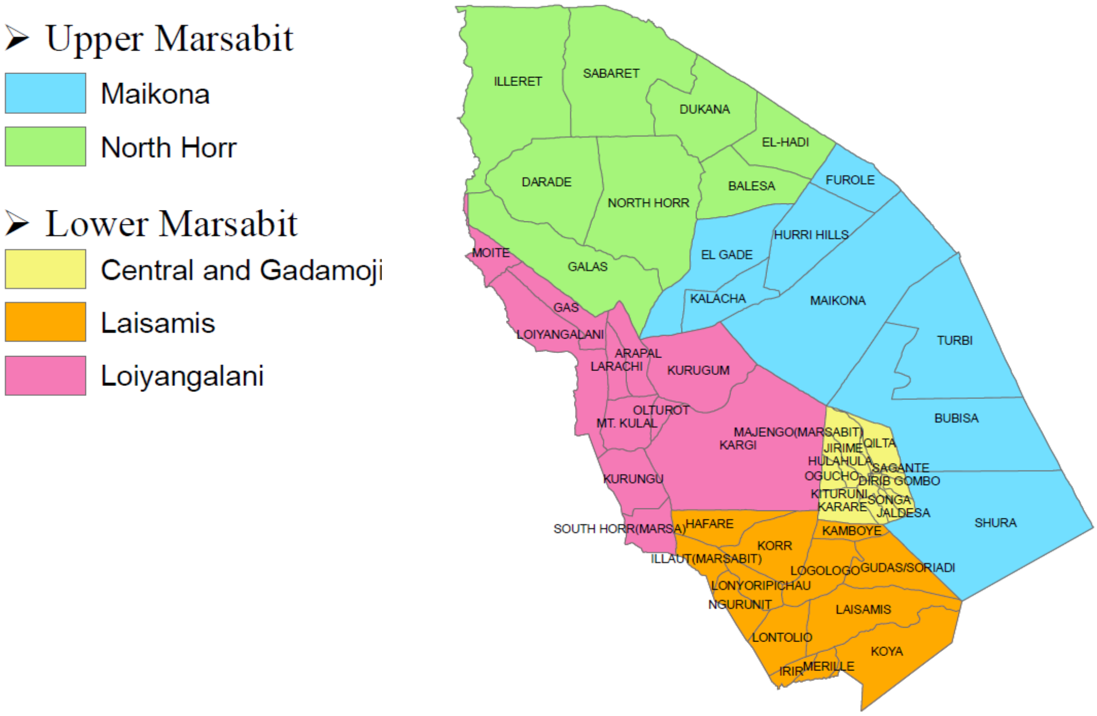

Figure 14 Study Area in Marsabit District

Source: IBLI web site http://ibli.ilri.org

4.2.2 Data

The data on child schooling, herd migration, and household characteristics are taken from panel data collected by the International Livestock Research Institute's (ILRI) Index-Based Livestock Insurance (IBLI) project, which implemented a baseline survey in 2009 in the Marsabit district of Northern Kenya, complemented by annual follow-ups from 2010 to 2013. For all these survey waves, information was collected in 16 sublocations (see Figure 14) using a sample proportionally stratified on the basis of the 1999 household population census. First, the researchers classified households into three wealth categories based on livestock holdings converted into TLUs low (<10 TLU), medium (between 10 and 20 TLU), and high (>20 TLU). Within each sublocation, one third of the location-specific sample was randomly selected from each of these wealth categories, which were then used to randomly generate a list of households. For replacement purposes additional households were randomly selected based on the wealth class that were to be used in case a household was to be replaced. For instance, if a low, medium, or high wealth household could not successfully be reinterviewed during subsequent surveys, it was replaced by an equivalent household, yielding a consistent sample of 924 households across all survey years.

Because few data are available on the transition from primary to secondary schools in the study area, our analysis is also restricted to primary school students aged 6 to 15. The low attrition rate in the sample reduces the potential bias from household migration. To capture school attendance, we use the responses in all survey waves on whether a child was currently attending school or not. The herd migration data, also obtained for all five survey waves, indicate whether households moved their animals away from home looking for grazing pastures at any given period in the course of that survey year. In defining the herd migration variable, we consider those that moved to one or more satellite camps versus those that did not move their livestock at all.

To understand community perceptions on schooling, we use data from focus groups discussions held at selected sublocations in the study area. The key objectives of these group discussions were to identify barriers to schooling, schooling decisions, schooling disparities between boys and girls, and community efforts to promote child schooling. The groups also discussed shocks experienced by the community in the previous 10 years (from 2005) and their impact on child schooling. The eight sublocations for the focus group discussions – Bubisa, Elgade, Kargi, Loiyangalani, South Horr, Ngurunit, Dirib Gombo, and Sagante – were sampled out from the 16 sublocations in the household survey based primarily on the prevalence of drought, homogeneity of rangelands, and livestock composition. Using these variables as a basis ensured an unbiased and representative sample. Each FGD comprised 8–10 community members from different backgrounds, including pastoralists, teachers, and opinion leaders, with a good representation of both men and women. The different sublocations also guaranteed a varied ethnic composition, including Gabra, Rendille, Turkana, Samburu, and Borana. Overall, the FGD data generated useful descriptive narratives that help to explain particular trends observed in the household panel data.

4.3 Descriptive Statistics

To provide an initial educational profile of the Marsabit district, we first report statistics provided by the county government on the state of education in 2014. At that time, Marsabit county had a total of 166 primary schools, with Moyale subcounty having the most at 54 and North Horr the fewest at 30. Primary school enrollment rates differed by subcounty, with Saku having the highest at 81.1%, followed by Moyale (56.5%), Laisamis (48.1%), and North Horr (32.2%). As Figure 15 shows, although primary school enrollment included more boys than girls overall, 2014 enrollment was higher for girls than for boys in Saku and North Horr subcounties. This difference suggests a regional disparity in school enrollment, as well as uneven distribution across gender. The student-teacher ratio was highest in Moyale (52.8:1), followed by Saku (38.87:1) and Laisamis (37.07:1), with North Horr again coming in lowest (34.57:1), which further indicates an unequal distribution of teachers across the different subcounties. Marsabit county overall has had to contend with several major challenges, including low student enrollment, high dropout rates, inadequate schools, insecurity, migration, and cultural practices like moranism[39] and early marriage that have lowered educational standards (Marsabit 2014).

To address the low enrollment, since 2014 the NGO Adeso implemented its Mobile Nonformal Education (MNFE) project to boost the literacy levels of children aged 13 to 18. This project follows nomadic children along their migratory routes in the remote grazing areas (far from formal schools) and provides them with a nontraditional class structure. In this scheme, learning is carried out every day at different times depending on learner availability, with some classes held in the early morning before the children go out to herd and others in the

[39] Between the ages of about 12 and 30, young men, traditionally known as morans, live in isolation in the bush learning tribal customs and developing strength, courage, and endurance

evening after they return from the fields. The aim is to eventually transition the pupils into the formal schooling system (Adeso 2015).

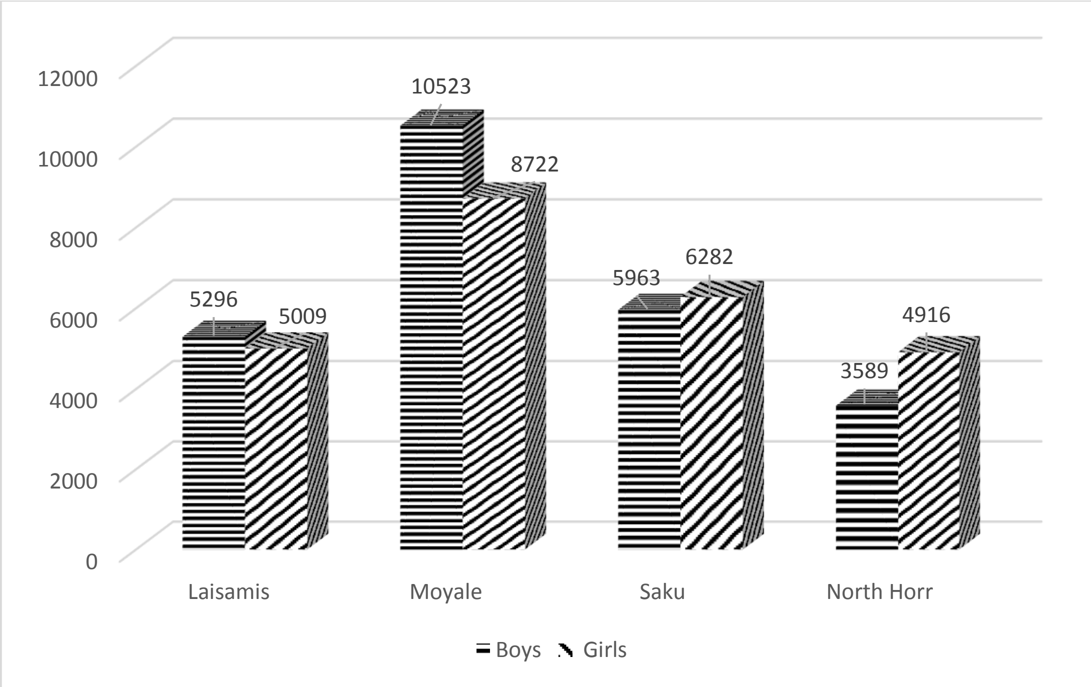

Figure 15 Primary school enrollment by gender in Marsabit county 2014

Source: Marsabit County report (2014)

The household data used for this study cover some areas in Laisamis, Moyale, and Saku subcounties over the five study waves. The key analytical variables are summarized in Table 25, which reveals an average school attendance of 62.9 %, with an increasing trend from 56.8 % in 2009 to 65.6 % in 2013 for an average enrollment age of 6.1 years (for enrollment age distribution, see Appendix 7). Disaggregating by enrollment age yields 6.2 and 6.0 years for boys and girls, respectively. This increased school enrollment may in part be the result of the government's free primary education and school lunch programs in arid areas, which help keep children in school. The upward trend may also be partly driven by the negative effects on pastoralism of the frequent recent droughts (UNICEF 2006).

Table 25 Summary of key variables for the pooled data

Variable	Full	2009	2010	2011	2012	2013
Attending school (%)	62.9	56.8	62.0	63.4	66.8	65.6
Male child (%)	52.8	53.4	53.1	53.0	52.3	52.4
Age child (years)	11.1	10.7	10.7	11.3	11.3	11.4
Herd migrated (%)	73.8	64.7	77.9	74.9	76.2	75.4
Household size	7.2	7.1	7.1	6.9	7.6	7.6
Male-headed household (%)	63.5	62.9	62.0	62.8	64.9	64.9
Age of head (years)	50.0	50.3	50.0	49.6	50.1	50.0
Head sick (%)	17.7	18.6	14.3	17.1	18.0	20.5
Education of head (years)	0.9	0.9	0.9	0.9	0.9	0.9
Spouse literate (%)	7.9	8.0	7.6	8.4	7.7	7.8
Total TLUs	14.3	17.3	17.2	11.4	12.0	13.0
Purchased insurance (%)	14.5	0.0	28.1	26.9	9.0	9.0

Note: The data are for children aged between 6 and 15 years for each survey wave (N=8,642)

When we disaggregate by gender, school attendance increases from 56.4% to 63.6% among boys and from 56.9% to 69.0% among girls, possibly as the result of a spirited formal education campaign by the government, local administrators, and Non-Governmental Organisations (NGOs). These agencies also discourage parents from early marriage for girls. For the children who have never attended school, the main reasons tend to be domestic duties like caring for younger siblings and cooking (38.7%), contributing labor for household production (28.3%), and being too young (14.0%). It is also worth noting that affordability does not rank among the primary reasons for non-school attendance. In addition, as expected, the data show that the proportion of children attending school increases with age to a peak between ages 12 and 13 and then declines for both boys and girls. This finding of fewer children attending school at younger ages indicates a nonlinear relation between age and school attendance. There are also more girls attending school at young ages (between 6 and 9 years) than boys.

We then use pooled observations to further disaggregate school attendance by sublocation revealing higher school attendance in Dakabaricha, Dirib Gombo and Sagante, and South Horr, which are all located near town centers in which schools are more accessible. In the sublocations of Karare, Kargi, Kurkum, Lontolio, and Illaut, a higher proportion of girls attend school, possibly because strong cultural practices like moranism tend to keep boys out of school in these areas. The Illaut and Elgathe sublocations, respectively, show the lowest school attendance for boys and for girls.

The household statistics also identify herd migration as a common practice among the area population, with an average 74% of households across survey rounds moving their livestock to satellite camps.[40] The main reasons for herd migration are coping with drought (72.9%), better pastures (20.4%), and conflict between communities (3.68%). The education levels of both the heads of these households and their spouses is quite low, with the majority being illiterate. The pooled data further show that in 2014, the majority of students in the area were enrolled in government schools (90.9%), with only a few in private schools (2.2%) or nursery school (5.1%). The drop-out rate was quite low (<6 %), although higher among boys (5.4%) than girls (4.9%). Reasons cited for dropping out include provision of labor for household production (32.7%), student problems (20.3%), and temporary school closures (9.6%). The average days absent from school annually are 13.0 and 13.5 days for boys and girls, respectively, with student sickness (32.6%), temporary school closures (26.5%), and teacher absence (25.9%) being the primary reasons. These school closures occur primarily because of communal conflicts that keep teachers away from school. It is also worth noting that few children were absent to work in the household.

Across all survey rounds, the majority of students (92.1%) benefited from the school lunch program, which prompted us to also investigate how school attendance is affected by household food insecurity. This analysis identifies food aid (30.6%), reduction in the number of meals (24.2%), and assistance from others (13.6%) as the primary coping strategies for food shortages. Interestingly, it also indicates that pulling children out of school is not a major strategy (3.4%), implying that free school meals help keep children in school when food is scarce at home.

[40] "Satellite camps" are grazing areas to which pastoralists move their livestock for a given period.

4.4 Methodology

We model child schooling outcomes (school attendance) based on a set of child and household characteristics, with the schooling regression function expressed as follows:

$$S_{ijt} = \beta_o + \beta_1 C_{ijt} + \beta_2 H_{jt} + \beta_3 A_{jt} + \beta_4 R_t + \beta_4 T_t + \varepsilon_{ijt} \qquad (1)$$

where;

S_{ijt} is the schooling outcome for child *i* belonging to household *j* at time *t*;

C_{ijt} represents the child-specific characteristics;

H_{jt} represents herd migration for household *j* at time *t*;

A_{jt} represents the household characteristics for household *j* at time *t*;

R_t is a regional dummy;

T_t is a time dummy; and

ε_{ijt} represents the error term and other unobserved factors.

The dependent variable S_{ijt} is school attendance[41] (1 = the child is currently attending school, 0 otherwise). Herd migration H_{jt} is the main dependent variable of interest, with *i* as a dummy for whether or not a household moved its livestock (1 = moved livestock, 0 otherwise). The model also includes controls for child characteristics C_{ijt} such as age and gender, and household characteristics A_{jt}, which include household size, age and gender of household head, education level of head and spouse, and livestock owned. Negative household shocks are represented by the head of household being ill. To check for collinearity of the independent variables, we measure the variance inflation factor (VIF), whose low values for each variable (less than 5) suggests they are not closely related. The correlation coefficient between herd migration variable and livestock owned, although significant, is also quite low (0.27). The regional dummy, which covers Central and Gadamoji, Maikona, Laisamis, and Loiyangalani,

[41] Because school attendance refers to enrollment in the formal schooling system, children enrolled in religious schools are treated as not enrolled.

addresses regional differences in climatic conditions and herd composition, while the time dummy accounts for any potential effects of the respective survey year.

The regression model is specified in two ways: as a probit model for the pooled data and as a probit random effects model for the panel data. When using the pooled data, we assume no unobserved individual effects (an admittedly restrictive assumption) and specify the probit model as follows:

$$\Pr(Y = 1|X) = \phi(X^n\beta) \qquad (2)$$

where Pr denotes probability, ϕ is the cumulative distribution function of the standard normal distribution, and the β parameters are estimated by maximum likelihood. The left hand of the equation is a probability confined between 0 and 1. The variables used for this model are as specified in regression (1), and for better interpretation, we calculate the average marginal effects for all coefficients.

The random effects[42] probit model used for the panel data is designed to address potential unobserved heterogeneity in certain important characteristics that affect the herd migration-schooling relationship. The model, which assumes no correlation between unobserved heterogeneity and the independent variables, is specified as follows;

$$\Pr(Y_{S_{ijt}} = 1|C_{ijt}, H_{jt}, A_{jt}, R_{t,} T_t) \qquad (3)$$

This model estimates both time-variant (household characteristics) and time-invariant (child gender) independent variables using a maximum likelihood estimation. In doing so, it makes two assumptions: the correlation between two successive error terms of the same individual is constant $u_{it} = (0, \sigma_u^2)$ and the individual-specific unobservable effect is independent of both the error term and the independent variables.

[42] Estimation using a fixed effects probit model is not possible because of the incidental parameters problem, which makes it difficult to remove unobserved heterogeneity by time and thus demeans the data. Such estimation requires a large data set and sufficient variance for both dependent and independent variables (Wooldridge 2012).

4.5 Results and Discussion

The probit and random effects results are reported in Table 26, whose columns 1, 2, and 3 present the two sets of coefficient estimates and the marginal effects of the probit model, respectively. These outcomes suggest a significantly negative effect of herd migration on school attendance. For the most parsimonious model, the probability of a child's failure to attend school is 0.46 for a household that moves its livestock and decreases to 0.26 once other child, household, and time variables are controlled for. Similarly, with the other factors controlled for, the marginal effects indicate a 0.09 (9%) decrease in school attendance probability for children in these households. These pooled probit findings are generally supported by the probit random effects results: in model 4, with other factors controlled for, the probability of a child failing to attend school decrease by 0.43 (43%) for a household that moves its livestock. As before, child school enrollment is positively and significantly affected by parental education (both father and mother).

Table 26 Regression estimates of factors influencing child school attendance

	(1)	(2)	(3)	(4)
Dependent variable: School attendance (1 = yes)	Probit	Probit	Probit	XTProbit random effects
	Coefficient	Coefficient	Marginal effect	Coefficient
Herd migration (1 = yes)	-0.4672**	-0.2672**	-0.0918**	-0.4343***
	(0.235)	(0.112)	(0.038)	(0.087)
Child gender (1 = male)		-0.0551***	-0.0189***	-0.2224**
		(0.014)	(0.005)	(0.093)
Child age (in years)		0.0080	0.0027	0.0047
		(0.018)	(0.006)	(0.016)
Household size		0.0511***	0.0176***	0.1161***
		(0.006)	(0.002)	(0.021)
Gender of head (1 = male)		0.0479	0.0165	0.1827*
		(0.125)	(0.043)	(0.102)
Age of head (in years)		0.0030*	0.0010*	0.0120***
		(0.002)	(0.001)	(0.003)
Illness of head (1 = yes)		-0.0904***	-0.0311***	-0.0379
		(0.024)	(0.008)	(0.083)
Education of head (in years)		0.0790***	0.0271***	0.2247***
		(0.003)	(0.001)	(0.025)
Mother literate (1 = yes)		0.3560**	0.1224**	1.3475***
		(0.141)	(0.049)	(0.261)
Livestock owned (TLUs)		-0.0065***	-0.0022***	-0.0120***

		(0.001)	(0.000)	(0.002)
Constant	0.6867**	0.1788		-0.2969
	(0.304)	(0.143)		(0.268)
lnsig2u				2.80496
Sigma_u				4.06527
Rho*				.9429433
N	8993	8642	8642	8642
Adj. R^2				

Note: The data include all school-aged children from 6 to 15 years. Time and regional dummies are estimated but not shown. Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
*The output rho (0.94) shows the panel indicator to be better than the pooled estimator.

The results for the other control variables indicate that boys are less likely to attend school than girls, with an estimated coefficient that is negative and statistically significant. Household size, in contrast, is significantly positive, implying that children from larger families are more likely to attend school. The age of the household head is also positive and significant in both models; however, the illness of a household head is a major idiosyncratic shock that negatively influences both household income and the probability of child school attendance. Both the household head's educational level and the mother's literacy are significantly positive for the probability of school attendance: a child whose father has some schooling is 7% more likely to be enrolled in school. In our sample, however, although the mothers' knowledge contributes to household and school-related decisions, the majority of mothers have no formal education, so we include a dummy variable equal to 1 for some level of education and 0 for no education. The overall results suggest that educated parents are more likely than noneducated parents to enroll their children in school, a finding that conforms to similar studies showing that a higher level of household education has a positive impact on child schooling (Abafita and Kim 2014; Mani et al. 2013). The parameter estimates of total livestock owned in tropical livestock units is significantly negative, indicating that households with large herd sizes are more likely to have difficulty meeting labor demands and are thus more apt to have their children provide labor within the household, which ultimately has a negative effect on child schooling.

4.6 Grade attainment gap

Because grade attainment data were not collected in the four survey follow-ups, this analysis is based only on the baseline survey (2009). Using this dataset, we estimate relative grade attainment by dividing the actual grades completed by the potential grade, expressed as the total number of grades completed had the child completed grade one by age 7. These values range between 0.1 and 1.0, with higher scores indicating more schooling efficiency. Because these values take into consideration both class repetition and child enrollment age, they account for both enrollment delays and grade attained conditional on age. The mean relative grade attainment is 0.67 (implying 67% schooling efficiency), which indicates some level of inefficiency (33%), possibly due to high rates of grade repetition, high dropout rates, and/or late enrollment. Girls have a slightly higher grade attainment (0.69) than boys (0.66), perhaps because boys fail and repeat classes more than girls (Grant and Behrman 2010). The correlation coefficient between grade attainment and gender is -0.3, which confirms that boys are more likely than girls to repeat classes or drop out of school. Schooling efficiency by age group further reveals a 70% and 65% grade attainment for the 6–11 and 12–16 year age groups, respectively, implying a lower rate of class repetition and dropout in lower- versus upper-level classes.

To identify the determinants of whether children who have ever attended school stay in school longer (i.e., accumulate more school years), we estimate the factors influencing child schooling efficiency using an ordinary least squares (OLS) estimation. As Table 27 shows, younger children have a higher schooling efficiency than older children: a one-year increase in age reduces the relative grade attained by 0.015 points. This effect does not change even after we control for other household covariates. A child in an upper-level class is also more likely than children in lower-level classes to repeat classes or drop out of school. The household head's education level also has a significantly positive effect on relative grade attained: a one-year increase in household head's education raises the relative grade attained by 0.006 points, further indicating that educated parents are more likely to motivate their children to perform well and complete schooling. Conversely, herd migration and illness in either the child or the household head negatively affect schooling efficiency, although these effects are not statistically significant. Geographic location also has a notable impact: other factors remaining constant, children in Dakabaricha sublocation, which is located in Marsabit township with greater access to schools, are far less likely than children in the other 15 sublocations to drop out of school or repeat classes. These results underscore the significantly negative effects of dropping out and class repetition on child schooling efficiency.

Table 27 Factors influencing child schooling efficiency

	(1) OLS	(2) OLS	(3) OLS
Dependent variable = Relative school grade attained	Child characteristics		All covariates
Child age	-0.0157**		-0.0154**
	(0.004)		(0.004)
Child gender of (1 = male)	-0.0295		-0.0239
	(0.019)		(0.022)
Child illness (1 = yes)	-0.0209		-0.0133
	(0.027)		(0.027)
		Household characteristics	
Education of head (in years)		0.0068**	0.0062*
		(0.002)	(0.002)
Mother literate (1 = yes)		0.0061	0.0050
		(0.041)	(0.044)
Illness of head (1 = yes)		-0.0589	-0.0584
		(0.032)	(0.033)
Household size		0.0006	0.0017
		(0.006)	(0.006)
TLU owned		0.0007	0.0007
Move livestock (1 = yes)		-0.0018	-0.0013
		(0.019)	(0.019)
		(0.000)	(0.000)
Constant	0.8798***	0.6582***	0.8468***
	(0.039)	(0.028)	(0.056)
N	749	746	745
Adj. R^2	0.034	0.023	0.053

Note: Sublocation dummies are estimated but not shown; robust standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

4.7 Focus Group Discussions (FGDs)

To complement the household data on (barriers to) child schooling in the study area, we use community data collected from focus group meetings. These data focus particularly on barriers to schooling, changes in schooling over the last decade, and community efforts to promote schooling.

4.7.1 Barriers to schooling

The focus group participants reported the following numbers of public primary schools in the respective sublocations: Dirib Gombo (2), Sagante (1), Bubisa (2), Elgade (1), Kargi (4), Ngurunit (2), South Horr (3), and Loiyangalani (4). They also identified three major barriers to schooling: accessibility, affordability, and cultural practices and perceptions. As regards the first, group members complained that in most locations, schools are so few that children must walk long distances to reach the nearest institution. For example, even though Elgade sublocation covers a very expansive area, it has only one public school, which adversely affects the children's learning opportunities and school performance. The participants thus argued that establishing more boarding schools would eliminate the need for long commutes to school and increase enrollment. School attendance is also hindered by the relatively high poverty levels among the households, which makes the cost of books and school uniforms prohibitive even when education is offered for free. Certain cultural practices also act as barriers to schooling. For example, in the Gabra community, firstborn boys are required to stay home from school during cultural events like the "sorio" passover ceremony and cultural "new months." Moranism also keep young boys from school as they learn about their cultures and develop endurance in the bush for a considerable long period of time. This absence is in line with the findings from the regression analysis, which show boys as less likely than girls to be attending school. The household's nomadic lifestyle also means migrating to other areas in search of grazing pastures, which forces some children to drop out to provide labour. This observation corroborates the results from the household survey data, which indicate that herd migration negatively affects schooling. The participants further noted that some households are reluctant to enroll their children in school because they see no benefit in education and prefer them to learn informally about local lifestyles so as to perpetuate existing social norms and values. In some areas, children are engaged in paid labor activities such as herding or small businesses that provide alternative income for their families, and school-aged girls may be given into early marriage and pregnancy.

4.7.2 School attendance among boys and girls over the last decade

The participants did note, however, that over the last 10 years, there has been a general increase in school attendance among both boys and girls. The reasons for this increase include the government's implementation of free primary education, a law that local administrators have keenly enforced, and an increased sensitization among community members of the importance of education. As one participant in Bubisa noted, "We have to make the crucial decision between sending children to school and losing out on production, or keeping them here where they cannot engage with the outside world." The participants did agree, however, that, as suggested by the regression finding of higher enrollment and higher grade attainment among girls, the rate of school attendance among girls has been increasing relative to that of boys. One possible explanation is the affirmative action measures implemented by the government and other agencies, which emphasize girl child education to escape early marriage and female genital mutilation. Conversely, the groups noted a laxity in promoting formal education among boys, which is hindered by certain cultural traditions (e.g., moranism among the Rendille and Samburu). The tendency of girls to remain at home, in contrast, facilitates their school attendance.

When boy are not in school, their main activity is herding, and because livestock is the community's primary means of support, many argue that unless boys tend to the livestock, the entire community risks losing its livelihood. The payment for livestock herding is either in monetary value (typically around 2-4 thousand Kenyan shillings a month) or in kind; for example, one cow or camel (female) for having herded the livestock for one year or a lesser valued sheep or goat (female) for having herded it for a period of less than six months. Losing this income is the opportunity cost of sending boys to school. If a household hires a herdsboy and compensates him with livestock, losing this livestock is the cost of their children's education. They also lose out on the other casual labor performed by boys, such as sand harvesting and road construction. These losses and the substantial opportunity costs of schooling may partly explain the lower enrollment rates for boys. Girls, on the other hand, spend their out-of-school time in such household duties as washing clothes, fetching water and firewood, and cooking, activities on which the participants could place no monetary value. This inability to monetize is itself significant in that the failure to quantify household labor may mean that the opportunity costs for schooling girls are perceived as lower, which would explain greater enrollment among girls.

4.7.3 Community efforts to promote child schooling

As regards the increased community awareness of education's importance, the participants credited local leaders and elders who have taken it upon themselves to ensure that school-aged children are enrolled in school. These leaders encourage parents to facilitate learning by taking care of their children's educational needs, including books and uniforms. Educated members of the community also visit the schools as role models to motivate the children. As one teacher participant from Bubisa noted, "I am happy to teach in the community and be a role model. It does not help anybody to keep education to oneself." There was also consensus that although the majority of pastoralists are aware and appreciative of the importance of sending their children to school, they face several challenges to doing so, including an inadequate number of schools and a lack of facilities and teaching staff. In some locations, parents address the problem of teacher shortage by supporting volunteer teachers who are paid through community contributions.

4.7.4 Drought and child schooling

The focus participants also commented on the increased frequency and intensity of drought over the past few decades, leading to increased reliance on food assistance. For example, all sublocations had experienced frequent droughts over the previous 10 years, with the most severe occurring in 2009 and lasting until 2011. During this period, the communities incurred major livestock losses from starvation and disease, which led to food shortages and hunger in a majority of households. Traditional ways of coping during drought periods include migrating with livestock, diversifying livelihoods to business and petty trading like firewood sales, and forming social groups that teach local grazing land management and/or promote the importance of selling livestock prior to drought. Households also engage in meal reduction (amount and frequency) and consumption of nonstaples like wild fruits (e.g., "deka"). In some instances, they can purchase food items from local shops and pay later at minimum interest rates. Parents may also keep children home from school to assist in casual work while they themselves look for food or may even send some children to live with relatives. The institutional coping mechanisms are mainly food aid, cash transfer, and food for work from both government and nongovernment agencies. There is also a post-drought livestock restocking program though which a household receives a female cow to compensate for lost livestock. Some areas also have supplementary feeding programs that target pregnant and lactating mothers, as well as malnourished children under five. Certain households also benefit from the livestock insurance being implemented in the region with the aim of compensating herders for drought-related livestock losses.

The effect of drought on child schooling is quite profound. Because they are not eating enough, children may be too enervated to concentrate on their classwork or may even fall sick and end up missing school. Because drought may also encourage families to send their children to relatives, these periods are also characterized by higher dropout rates. Whereas some children drop out to engage in casual jobs, others look after the home while their parents seek casual labor. Boys, being more involved in herding, often have to move with the livestock in search of grazing pastures, while school aged girls may be married off to bring in bridewealth with which to buy food and other household necessities. Participants in the Kargi sublocation, for example, estimated a bride price at about 8 mature camels, worth approximately half a million Kenyan shillings. These early marriages bring the girls' schooling to an end, denying them the opportunity to better their lives through education.

In addition, drought conditions tend to set in after the prolonged June to September dry season, which coincides with the children being in school (the school holiday months are April, August, and December). Because in drought periods, the local communities face acute food shortages, livestock migration in search of grazing land is also common during dry seasons. Yet, as the participants observed and our household data indicate, the free meals provided in schools play a crucial role in children attendance, benefitting about 92% of the pupils in our analysis. In addition to improving attendance, these meals save the children a journey home for lunch, which reduces household food expenditure, allows uninterrupted learning, and conserves time and energy that can then be concentrated on school work.

4.7.5 Intercommunal conflict

The group participants also lamented the spontaneous intercommunal conflicts in the region over such political and community interests as watering places and grazing pastures. In Kargi and Elgade sublocations, for instance, the Gabra and Rendille communities have clashed persistently over scarce grazing land and watering holes, with tribal enmity peaking in 2007 and 2009. Similarly, in South Horr and Loiyangalani, conflict between the Samburu and Turkana communities, mainly at the onset of the long rainy season, has resulted in loss of life and property. During these incidents, raiders may steal livestock, which adversely affects the victims' livelihoods and in some instances even forces households to relocate in fear of attack. The effects of these conflicts on child schooling are significant, with schools closing for long periods and families displaced to securer areas. Both these events force children out of school and may result in eventual dropout. The rival communities should thus try to settle these disagreements by engaging in peace talks and dialogue.

Overall, the focus group data indicate a positive attitude to child education among the participants, with clear recognition of individual and community efforts to promote schooling even at the expense of production. In fact, despite too few schools and learning-conducive environments, the determination to improve educational standards in these marginal areas is enviable. The group discussions also highlighted, however, that if communities are to achieve their goals by reconciling a pastoral lifestyle with the pursuit of formal education, specific actions are necessary: First, the government should set up more schools, increase teaching staff, and improve the infrastructure of existing schools. Second, it should provide mobile schools to reach children in far flung areas.

4.8 Conclusions

After first estimating school enrollment and attendance among boys versus girls and identifying how they are affected by herd migration, this study summarizes representative community members' perceptions of schooling and pinpoints both barriers to education and community efforts to overcome them. According to the analytic results, the effect of herd migration on school attendance is significant and negative: once other factors are controlled for, the predicted probability of child failure to attend school is 26% for households that migrate their livestock. On the other hand, attendance is positively impacted by the educational level of both the household head and his spouse. At the same time, boys are less likely to attend school than girls, probably, the FGD participants confirmed, because boys engage in more economically valued activities like herding, which raises the opportunity costs of their absence for school. Girls, in contrast, engage mostly in nonmonetizable household duties. Nevertheless, as key barriers to school attendance, the participants identified too few schools, nomadism, and communal conflicts.

The analysis of survey data does indicate that over the five years studied, school enrollment increased for both boys and girls, averaging 63.6% and 69.0%, respectively, in 2013. During the same period, the school dropout rate was quite low (less than 10%) although still higher among boys than among girls. The mean schooling efficiency (relative grade attained) was 0.67, which implies inefficiency in grade progression. Girls were better off than boys in terms of both grade attainment and staying in school, while children from more educated families showed a higher schooling efficiency than those from less educated families.

Despite this apparent improvement in enrollment, however, the study suggests a definite need to increase school attendance and completion rates. To achieve this aim and ensure that pastoral children are not excluded from formal education, the government needs to implement education programs that fit the communities' nomadic lifestyle. Most particularly, in addition to erecting more schools, it should consider mobile schools for more remote areas. On a local level, the county governments and NGOs should assist communities to reconcile the formal education that traditionally occurs in fixed locations with informal cultural learning practices like moranism, which involve migration. They should also organize regular peace meetings across different communities to address the persistent conflicts that displace families. Both policy makers and assistance agencies should also consider designing and implementing interventions that contribute positively to child education by raising the literacy levels of parents and improving family welfare. Such measures should ultimately lead to better educated pastoral communities.

Chapter 5: Summary of findings

The following section gives a summary of findings. In chapter one we identified the levels, sources, and trends of household incomes across the five survey waves. We also estimated and compared the income and asset poverty levels. Income poverty was estimated using imputed household income relative to the adjusted poverty line and asset poverty using a regression-based asset index and tropical livestock units (TLU) per capita. Our results indicate that keeping livestock is still the pastoralists' main source of livelihood, although there is a notable trend of increasing livelihood diversification, especially among livestock-poor households. Majority of the households (over 70%) are both income and livestock poor with few having escaped poverty within the five-year study period. Disaggregating income and asset poverty also reveals an increasing trend of both structurally poor and stochastically non-poor households. The findings show that the TLU-based asset poverty is a more appropriate measure of asset poverty in a pastoral setting.

In chapter two we explored the household welfare dynamics among pastoral households in the study area. First, we developed a microeconomic model to analyze the impact of a shock (e.g., a drought) on the behavioral decisions of pastoralists. Secondly, we estimated the existence of single or multiple dynamic equilibria that may constitute an asset poverty trap. We used the tropical livestock units (TLUs) to establish the shape of asset dynamics to locate the welfare equilibria for the sampled households. We also estimated the household characteristics and covariate environmental factors that influence livestock accumulation over time. We use both non-parametric and semi-parametric techniques to establish the shape of asset accumulation path and determine whether multiple equilibria exist. From the model, we found that a negative shock like a drought leads to an immediate decrease in livestock followed by a smooth reduction in consumption. Because the shock also affects the local economy, it prompts a wage decrease, which reinforces the pastoralist's incentives to tend his own livestock and reduce time spent in the external labor market. Whereas the pastoralist's labor time allocation shows a pattern of quick convergence, however, the adjustment of other variables such as consumption and capital takes much longer. Food aid helps in smoothening consumption especially among households with few livestock. We established that livestock assets converge to a single stable equilibrium implying that households remained livestock poor in the short term. Such convergence to a stable equilibrium could result from households with more livestock smoothening their consumption during times of food shortage by drawing on their herds for sale or consumption while livestock poor households smoothen their assets by using coping strategies that do not deplete their few livestock holdings. Poor households thus destabilized their consumption to buffer and protect their few assets for future income and survival. We also found that forage availability and herd diversity influenced livestock accumulation over time.

In chapter three we established the extent of malnutrition among children by analyzing the levels of malnutrition among children aged five years and below. Additionally, we estimated the effects of drought, measured by the Normalized Difference Vegetation Index (NDVI), on child health outcomes. When the lack of sufficient rainfall reduces the levels of vegetative greenness, the corresponding lower NDVI values indicate forage scarcity. We followed the approach by Chantarat et al. (2012) and transformed the pure NDVI values to z-scores. We used the average NDVI Z-score values from long dry season (June, July, August, and September) for each survey year, extracted from four regions within Marsabit District. We then proxied the nutritional status of children using the mid-upper arm circumference (MUAC). We adjusted the MUAC for the age and sex of the child by converting the values to a MUAC Z-score based on WHO growth charts, as Z-scores are found to be better indicators of wasting than the fixed cut-off value (WHO 2009). The results show that malnutrition among children is prevalent in the study area, with approximately 20% of the children being malnourished and a one standard deviation increase in NDVI *z*-score decreases the probability of child malnourishment by 12–16 percent. The livestock insurance seems to be an effective risk management tool, as it slightly reduces the probability of malnutrition among children. Child health is also impacted by local conditions and family characteristics, which leave older children worse off than younger siblings who are still being breastfed or receive better care. In the most vulnerable households, boys are worse off than girls. At the same time, male-headed households tend to have healthier children, while family size is negatively associated with child MUAC. To reduce the effects of drought on child malnutrition, the targeting of food aid beneficiaries is crucial, and the use of remote sensing data could improve the effectiveness of these interventions.

In chapter four we sought to understand the levels of school enrolment and gender differences in schooling given the challenges of accessibility to schools in the pastoral areas. First, we established levels of school enrolment by gender. Secondly, we estimated the effect of herd migration on school attendance and thirdly we gathered the community perceptions about challenges that school going children face and how they can be addressed. We used both household panel data for children aged between 6 and 15 years and community data obtained from some focus group discussions. Results showed that the effect of herd migration on school attendance is significant and negative: once other factors are controlled for, the predicted probability of child failure to attend school is 26% for households that migrate their livestock. On the other hand, attendance is positively impacted by the educational level of both the household head and his spouse. The analysis of survey data indicates that over the five years studied, school enrollment increased for both boys and girls, averaging 63.6% and 69.0%, respectively, in 2013. During the same period, the school dropout rate was quite low (less than 10%) although still higher among boys than among girls. The mean schooling efficiency (relative grade attained) was 0.67, which implies inefficiency in grade progression. Girls were better off than boys in terms of both grade attainment and staying in school, while children from more educated families showed a higher schooling efficiency than those from less educated families. At the same time, boys are less likely to attend school than girls, probably, the FGD participants confirmed, because boys engage in more economically valued activities like herding, which raises the opportunity costs of their absence for school. Girls, in contrast, engaged mostly in nonmonetizable household duties. Nevertheless, as key barriers to school attendance, the participants identified too few schools, nomadism and communal conflicts.

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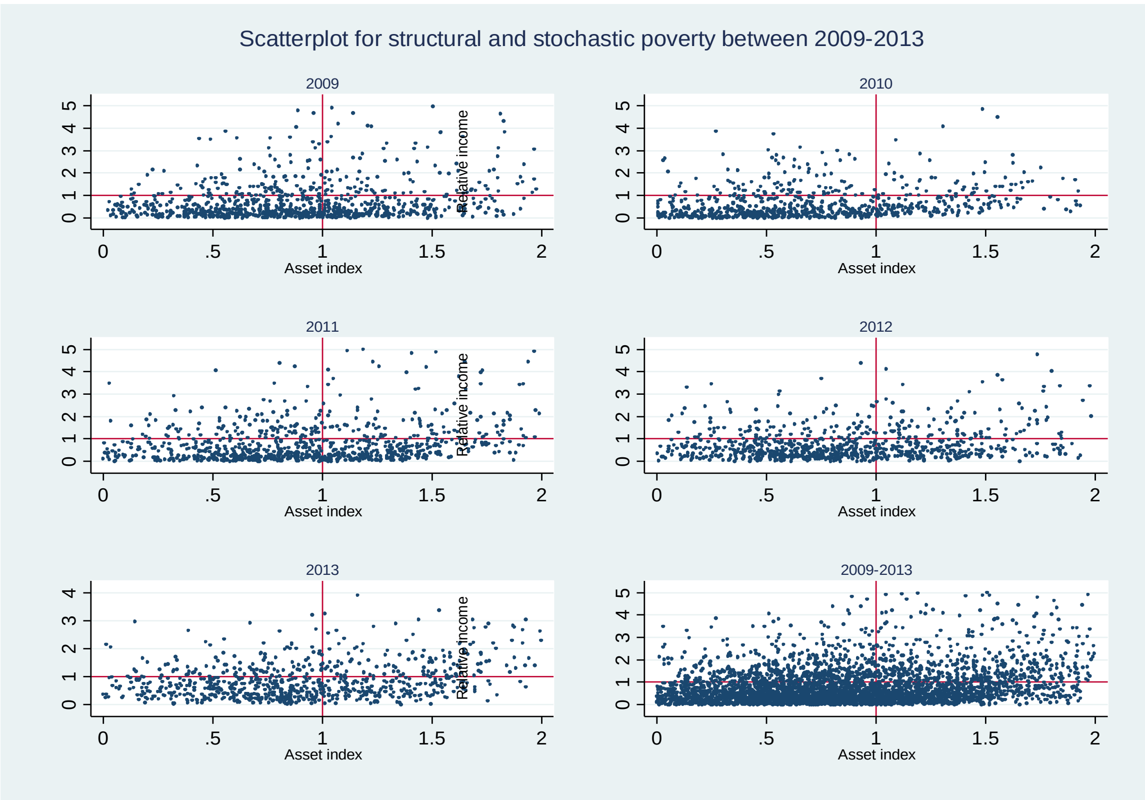
Appendices

Appendix 1 Adjustment of 2006 poverty line for inflation

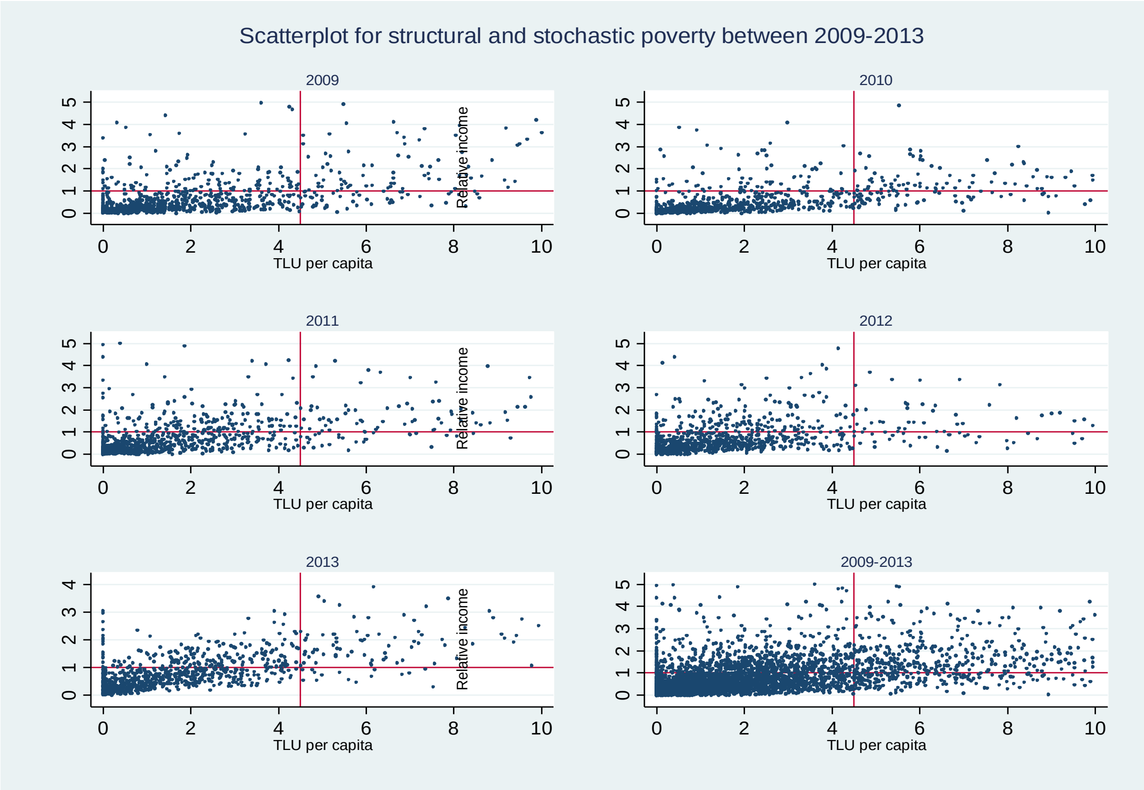
Year	Adjusted rural Poverty line (base year 2006)	Annual Inflation rate (%)
2006	1562	-
2007	1629	4.3
2008	1874	15.1
2009	2072	10.5
2010	2157	4.1
2011	2458	14.0
2012	2690	9.4
2013	2843	5.7

Source: own computation using data from the Kenya National Bureau of Statistics (KNBS)

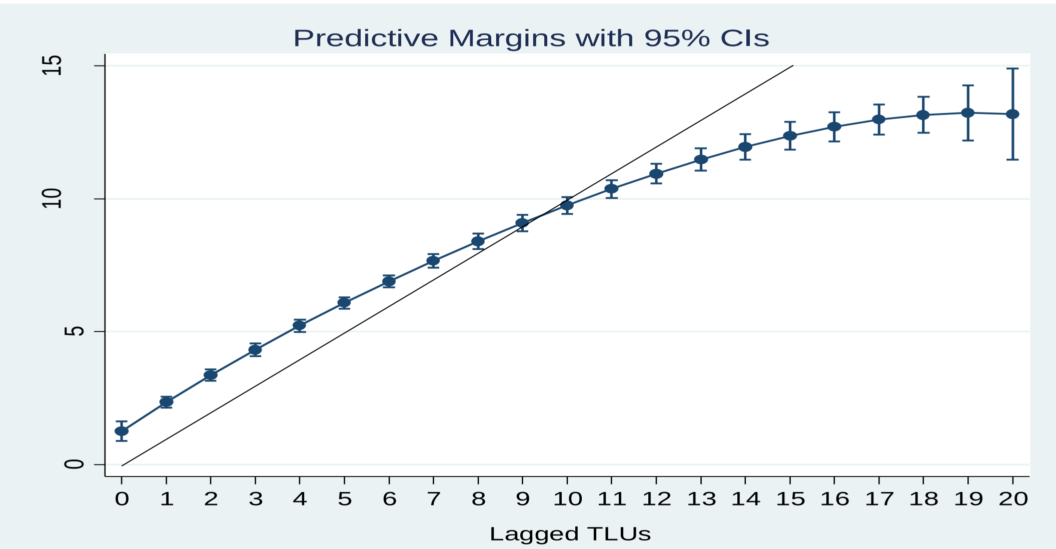
Appendix 2 Scatter plots based on the asset index



Appendix 3 Scatter plots based on the TLU per capita

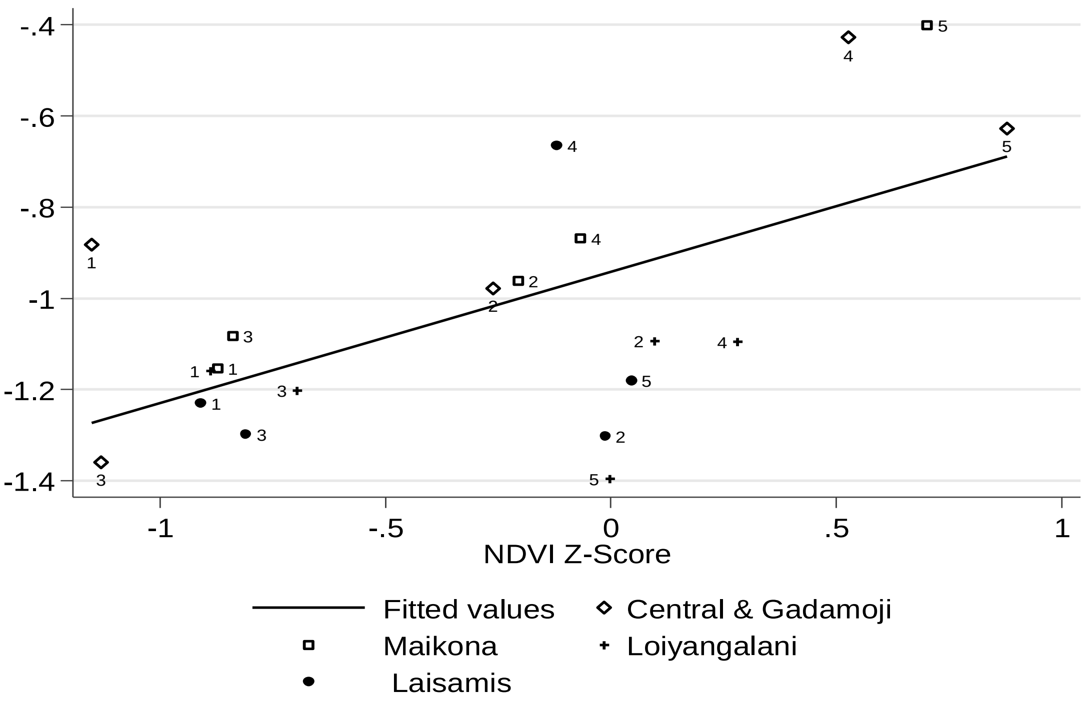


Appendix 4 Fourth-order polynomial prediction of lagged livestock assets

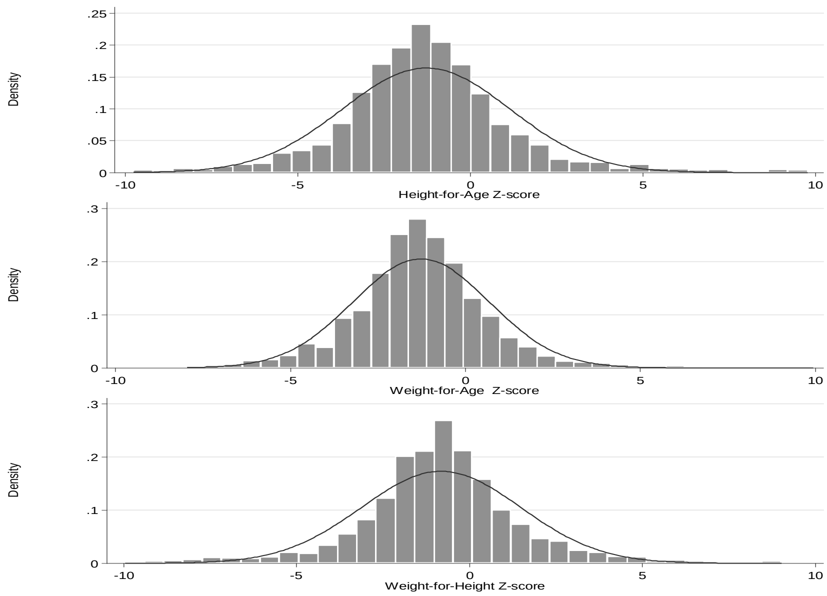


Note: Four-year lagged livestock in TLUs (2009–2013)

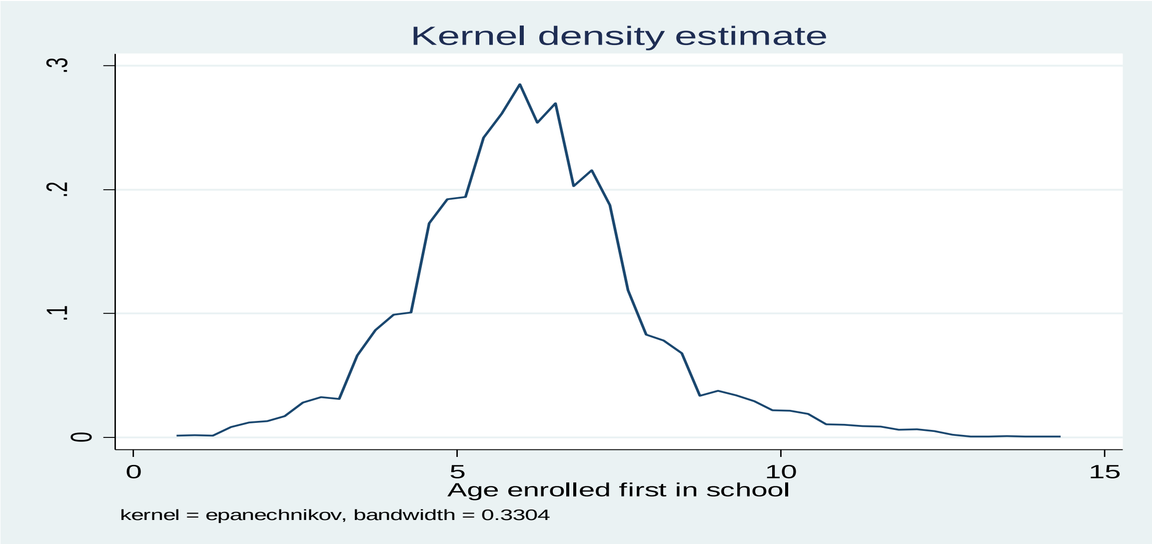
Appendix 5 NDVI and MUAC on the regional level



Appendix 6 Distribution of weight-for-age, height-for-age, and weight-for-height *z*-scores



Appendix 7 Age of school enrollment



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Duties:

- Contributing to the design of the IBLI research for development agenda (survey instruments, data collection and analysis) in Kenya and Ethiopia
- Overseeing management of IBLI project data
- Preparing comprehensive survey codebooks that fully describe the survey design , data collection methods, cleaning and inventory process
- Writing research reports and journal papers

March 2010- August 2011: Research Technician, Poverty Gender and Impact team, International Livestock Research Institute, Nairobi, Kenya

Duties:

- Analyze gender differentiated household surveys on livestock assets and products and their implications on household welfare outcomes as well as impact of increasing commercialization and formalization of livestock value chains on women's incomes and assets in Kenya, Tanzania and Mozambique
- Analysis of the actual and potential impacts of livestock and natural resource management-related interventions on household and community welfare in Gambia, Mali, Guinea and Senegal under the Global Environmental Facility Project

March 2002- February 2010: Research Assistant, Tegemeo Institute of Agricultural Policy and Development, Egerton University, Kenya

Duties:

- Designing data collection instruments including training manuals and questionnaires
- Recruitment and training of enumerators and field supervisors
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Computing Skills:

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Peer-Reviewed Journal Papers:

Waithanji E, Njuki J, **Mburu S**, Kariuki J and Njeru F, (2015). A gendered analysis of goat ownership and marketing in Meru, Kenya, *Development in Practice*, 25:2, 188-203

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Signature:

Declaration of Authorship

Declaration in lieu of oath in accordance with § 8 paragraph 2 of the regulations for the degree "Doctor of Economics" at the University of Hohenheim.

1. I, Samuel Kahumu Mburu, declare that this thesis on "Income and Asset Poverty Dynamics and Child Health among Pastoralists in Northern Kenya" and the work presented in it is my own and has been generated by me as the result of my own original research.

2. I have the approval of my co-authors to use the joint work in this dissertation and they endorse my individual contribution to the respective article.

3. I have used no sources or auxiliary means other than the ones acknowledged in this dissertation. I also have not used the illegal support of a third party, such as the help of a professional dissertation agency or consultancy. Where I have quoted from the work of others, the source is always given.

4. I affirm that the digital version submitted to the Faculty of Business, Economics and Social Sciences is identical to the hard copy.

5. I am aware of the meaning of this affirmation and the legal consequences of false or incomplete statements.

I hereby confirm the correctness of this declaration. I affirm in lieu of oath that I told the absolute truth and have not omitted any information

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Signature: