LUND UNIVERSITY
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Master in Economic Development and Growth

Insuring Kenyan Smallholder Farmers Against Drought: Does Livestock Index-Based Insurance Increase Climate Resilience?

by

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Abstract: While index insurance has received increased attention as an instrument for adaptation to climate change, evidence supporting its effectiveness remains limited. This thesis explores the potential of normalized difference vegetation index (NDVI) based livestock index insurance in Northern Kenya to help small-scale farmers to manage climate change risks in the event of livestock-reducing drought. This research uses the corresponding longitudinal data for 924 households over six rounds between 2009 and 2015. The conducted analysis seeks to identify (1) which household characteristics influence the IBLI product take-up and (2) whether a households' insurance status affects its income and consumption levels in the case of livestock loss from drought. Results indicate that subsidies and daily mobile phone access influence IBLI product take-up. We find little evidence supporting the value of IBLI as a useful tool to manage climate change risks from its measured impact on income and consumption. Overall, findings show that index insurance as a relatively new climate management tool faces considerable start-up challenges, to which new digitalization and funding techniques could provide solutions.

Key words: index insurance, microinsurance, livestock insurance, climate risk management

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1 Introduction

70 million people live in East Africa’s dry-lands and rely on rainfall for pastoralism, the main form of livelihood in the region (Mude, 2014). Northern Kenya has experienced 28 major droughts over the past 100 years, 4 of which occurred in the early 2000’s alone, directly impacting livestock and forcing over one million pastoralists to give up their way of life. These events have put considerable pressure on food aid among other emergency assistance as the traditional ex post response to extreme weather events (Adow, 2008; Mude et al., 2009).

The strong correlation between livestock mortality and drought mean that covariate risk continues to increase with the rise of extreme weather events (Barrett, 2011). These trends have driven interest for new ex ante risk management strategies that reduce household’s vulnerabilities before these events take place. Among these trends is insurance. Although different forms of agricultural insurance have been a common risk transfer tool in Western agriculture since the 19th century, they are uncommon in developing regions (Smith & Glauber, 2012; Wang et al., 2013). The high administrative costs and transaction costs are among the limitations that have halted the expansion of ‘indemnity-based’ or ‘claim-based’ agricultural insurance to these regions (Tadesse et al., 2015).

Index insurance has received growing attention as an alternative climate risk reduction tool functional for developing regions that overcomes these limitations (Greatrex et al., 2015). A number of large-scale initiatives have supported different types of index insurance programs across developing regions. Its basis is a predetermined index that proxies for agricultural loss using weather or yield indicators. Payouts for insured households occur when the predetermined thresholds of the index are surpassed. The few empirical cases have demonstrated low demand for index insurance products due to the height of premium and further switching costs for customers, although these are lower than for other agricultural insurance forms (Binswanger-Mkhize, 2012). High basis risk increases premiums and contributes to overall design difficulties of the index, debates regarding ecological impacts also exist (Peterson 2012; Wang et al. 2013; Tadesse et al., 2015; John et al., 2017). However, these challenges are not surprising considering the relative novelty of the product.

The possible benefit of providing agricultural insurance to developing regions, particularly to smallholder farmers that are climate-risk prone, provides a stong incentive to further the empirical inquiry into index insurance. Further evidence such as presented in this paper may also pave the way for improvements or opportunities for more successful index insurance delivery.

This paper aims to explore whether index insurance represents a viable solution to climate risk faced by smallholder farmers. Whether this form of insurance indeed serves its purpose as a climate resilience building tool is too broad of a question to tackle considering the many different index insurance types and implementation contexts. Instead, we focus on the case of the Index-Based Livestock Insurance (IBLI) program implemented in Northern Kenya and how index insurance affects these pastoralist household’s capacity to deal with drought. The central research question is as follows:

Does the Index-Based Livestock Insurance (IBLI) program propose a viable solution to smallholder farmer’s drought vulnerabilities in Kenya?

Next to the improvement of knowledge on the applicability on formal risk management strategies through new technologies, the focus of this essay notably lies in improving understanding of smallholder farmers needs and use for a tool as index insurance for climate resilience. Our hypotheses focus on two reoccurring sections of the index insurance literature, which addresses its demand and effectiveness.

1) The loss of livestock due to drought positively affects the likelihood of acquiring the IBLI product.

2) A IBLI insured household does not experience the same income loss and consumption decrease as an uninsured household does when suffering loss of livestock due to drought.

Our first hypothesis stems from the described problem of index insurance demand and the possible influence of weather predictions (Jensen et al., 2016). The hypothesis states that households which experience an adverse shock to their livelihood, which is composed of livestock, are more likely to adopt index insurance. This relates directly to our research question as it addresses whether households select this tool to increase their resistance to droughts. By testing this, we would like to understand what factors influence household's likelihood to adopt an index insurance product such as IBLI. A positive result of our hypothesis could confirm the need for and willingness of households to buy formal index insurance for risk reduction. Beyond this we also explore other household characteristics and their linkages to demand to provide a more comprehensive understanding of what factors drive up-take of IBLI.

Our second hypothesis relates to the outcome of insured households. We define the resistance of a household to an adverse shock as the ability to eliminate or reduce the effect of a shock through index insurance. This effect is measured through two components of the household economy, income, as source of assets, and consumption, representing the liquidation of assets. By analyzing these aspects, we estimate whether a household is affected differently when being covered by IBLI in the case of livestock loss due to drought shock.

To the best of our knowledge, the index insurance literature has not addressed these two outcomes in combination, rather, only a specific outcome or demand factor has been explored. We contribute to the index insurance literature by providing a comprehensive image of both uptake circumstances and resulting outcomes of the IBLI product. Furthermore, the literature is still primarily based on short pilot cases, this research is based on the longer case of the IBLI product implemented over 6 consecutive years and explores solutions and avenues of opportunity for successful prospective index insurance programs.

The structure of this paper is as follows. We begin in Section 2 with a literature review that introduces index insurance in the context of former agricultural insurance types, describes its advantages as well as disadvantages. Empirical cases of index insurance and the larger political economy debate provide local and global context to the larger discussion on the topic. The following Section 3 deals with the IBLI case, providing an overview of our case as well as the design of the index insurance product in question. The fourth part of this paper is the data section that discusses different aspects of the longitudinal data and provides summary statistics and data limitations. Subsequently, in Section 5, the methodology addresses the two hypothesis with two separate models whose results are presented and discussed in the following Section 6. The paper is concluded with the main findings of our study, its implications, and the addresses possible future research directions.

2 Literature

2.1 Agricultural Insurance

It is expected that climate change will disproportionately impact the sector whose inputs depend most on climate, agriculture. As the primary source of food, agriculture is essential to human survival. The increase of droughts and other climate-related events resulting from unusual climate patterns particularly in developing regions is alarming for agriculture and therefore human life (UNFCCC, 2018).

The agricultural sector is especially vulnerable to climate change dependency on weather patterns. Climate variations are the largest source of production variations in developing countries (Howden et al., 2007). Particularly smallholder and subsistence agriculture in developing regions are expected to be hit hard by these variations, where numerous factors, including socioeconomic, political and demographic, limit adaptation capabilities (Morton, 2007). Described as "complex, diverse and risk-prone"(Chambers et al., 1989), smallholder agriculture in developing regions is location-specific, integrates numerous different livelihood strategies and is vulnerable to stressors extending beyond climate variation. The resulting difficulty of modeling the actual impacts of climate change in these regions is a challenge in itself, as is the creation of adequate adaptation strategies that can encompass their diversity (Morton, 2007).

The conditions necessary for a successful agricultural production are subject to different risks. The uncertainty linked to rising climate variations have increased interest for risk management strategies, which can be categorized as: 'risk mitigation, risk transfer, risk diversification, and retained risk management' (Yang, 2010). A common risk transfer tool is insurance, which allows a transfer of the risk of losses to an insurer. For the case of agriculture, the risk of production losses is transferred to another party. This ultimately leads to the reduction of vulnerabilities related to weather conditions.

This literature review focuses on a newly popular form of insurance known as index insurance or index-based insurance. We begin by introducing the background of agricultural insurance as an informal and formal risk management strategy. Following this, we explore index insurance as a new strategy through its observed advantages and disadvantages. A discussion regarding the adequacy of such a tool also relating to development ensues.

Risk is not a new phenomenon in agriculture. Rural communities and smallholder farmers have always had to deal with risks. Numerous informal risk management strategies already exist. Common are crop diversification, with which households plant different kinds of crops to protect against the fall-out of one crop, and labor diversification, when household members seek employment off the farm to reduce diversify in case the agricultural income source becomes affected (Hess & Hazell, 2013). Households also take part in informal risk sharing groups or receive community support through informal financial institutions such as carousel type savings mechanism 'merry-go-rounds'.

However, these strategies are often insufficient when serious losses occur. For one, diversification strategies may reduce risk, but it also reduces income as farmers trade their most profitable income option for lower risk options. Generally, low assets of households in rural communities also mean that repeated shocks can trap households in poverty (Carter & Barrett, 2006). Community mechanisms are also not ready to deal with the covariate nature of the climate shocks, as all households are affected and need support at the same time.

Formal agricultural insurance in its current form was first offered by private insurers in Germany in the early 19th century as a form of livestock protection. The relatively newer government engagement, in the form of subsidies, funding or other guarantees, in the United States and Japan spread to other developed countries from the 1950s onwards. Overall, the advance of agricultural insurance in the form of crop insurance mainly took place in developed countries through substantial public funding support which is still in place today (Smith & Glauber, 2012; Wang et al., 2013).

The following Table 1 provides an overview of some of the different agricultural insurance products available today. While indemnity-based insurance and crop-revenue is among the most popular in developed countries, index-based insurance has been advanced in different forms in both developed and developing regions. We next delve further into the topic of index insurance.

Table 1. Agricultural Insurance Product Classification

	Type of Agricultural Insurance Product	**Payout**	**Availability**
a)	*Indemnity Based Agricultural Insurance* (insurance payouts based on the actual loss at the insured unit level)		
1.	Named Peril	Percentage of Damage	Widespread
2.	Multiple Peril	Yield Loss	Widespread
b)	*Index based Agricultural Insurance* (insurance payouts based on and index measurement)		
3.	Area-Yield Index	Area-yield Loss	USA, India, and Brazil
4.	Crop Weather Index Insurance	Weather Index payout scale	India, México, Malawi, Canada, USA
5.	NDVI Index Insurance	NDVI Index payout scale	Mexico, Spain, Canada
6.	Livestock Mortality Index Insurance	Livestock mortality index payout scale	Mongolia, Kenya
7.	Forestry Fire Index Insurance	Ignition focus/ burnt area payout scale	Canada, USA
c)	*Crop Revenue Insurance* (insurance payouts based on yield measurement and crop prices)		
8.	Crop Revenue Insurance (CRI)	Yield and Price Loss	Limited to USA

Source: The World Bank - Ramiro Iturrioz (2009)

2.2 Index Insurance

Index insurance only became available in the early 2000s as weather station data and satellite information developed (Smith & Glauber, 2012). This relatively new insurance form insures customers against certain weather risks threatening asset loss. For agricultural index insurance, rainfall levels or temperatures levels often provide the basis for the index. A benefit payout to insured actors occurs when the threshold levels in the predetermined index are exceeded (IFC, 2018; UNFCCC, 2008). Shortly, the basis for insurance payouts are not the asset losses themselves, but rather the index which proxies these asset losses (Hochrainer-Stigler et al., 2014).

While the different index insurance types follow the same principle, they are applied to different agricultural inputs and are therefore known through a range of names; weather-based crop insurance (Wang et al., 2013), weather-index based insurance (Ricome et al., 2017), weather index micro-insurance (Isaboke et al., 2016) or rainfall insurance among others (Dercon et al., 2014). While we draw on literature from different examples of index insurance, our empirical analysis focuses on livestock index insurance or livestock mortality index insurance. Our particular example uses NDVI data to compute mortality rates of livestock and can, therefore, be considered as a combination of NDVI index insurance and livestock mortality index insurance.

This research focuses on the implementation of micro-level index insurance which focuses on smallholder farmers, which are considered to be farmers relying on family as the main source of labour. However, index insurance programs are also being delivered to larger entities, at the meso and macro level. While it is agreed that micro-level denotes the household-level index insurance (Barnett et al. 2008; UNFCCC 2008; Tadesse et al. 2015), the exact definitions of the meso-level is less clear. Meso-level index insurance is described as representing a product implemented at a community-level (Tadesse et al. 2015), others describe it as an intermediate or market-level scale (UNFCCC 2008; Alderman & Haque 2007) as it is directed at 'meso organisations' or enterprises such as banks or agricultural suppliers (Barnett et al. 2008). The macro-level of index insurance is mostly defined as operating on a country or government-level (UNFCCC 2008). Tadesse et al. (2015) and Alderman & Haque (2007) define it as a form of external assistance or large-scale insurance to organisations such as the World Food Program (WFP).

The African Risk Capacity (ARC) was established by the African Union (AU) to improve its member states capacities to handle extreme weather events or natural disasters. This is an example of a macro index insurance scheme that insures African countries by pooling climate risks across a geographically diverse region. The ultimate goal of this initiative is to provide faster, cheaper and more transparent response to disasters to prevent food security problems and transfers capabilities to African governments (ARC, 2018).

These examples illustrate the popularity of index insurance at different scales. For the purpose of this research, however, we will focus on the micro-or household-level of implementation. This is due to our focus on smallholder farmers as a vulnerable group to climate change as well as data availability for our empirical analysis.

2.1.1 Opportunities

Agricultural insurance is generally plagued by numerous costs that make its provision disadvantageous for insurers. These include moral hazard and adverse selection, caused by the asymmetry of information between buyers and sellers of insurance, as well as high administrative costs or transaction costs linked to retrieving customer information or assessing damages after weather variations. The main reason for the existence of such programs in developing countries is the large level of subsidies provided by Governments. This is not possible in developing regions where agricultural production relies mostly on smallholder farmers. These reasons make the implementation of most agricultural insurance programs unfeasible for insurers in developing regions, making success in this area for private insurers unlikely (Yang, 2010). Index Insurance provides possible solutions to these issues by addressing these limitations.

A clear advantage of index insurance is that it is triggered by a verifiable parameter for which data is relatively easy to collect. This results in the reduction of administrative cost makes the handling of claims easier, enables more rapid payouts and decreases information asymmetry (moral hazard and adverse selection) (UNFCCC, 2008; Tadesse et al., 2015). A further benefit is that index insurance enables the transferability of risk taken on by insurers to international financial markets through reinsurance (Binswanger-Mkhize, 2012; Yang, 2010).

Index insurance also provides numerous potential avenues for improvement. Such as the technological advancements in remote-sensing which are only accelerating, meaning that access to data from remote weather stations will improve, opening new opportunities to index insurance developments (Hochrainer-Stigler et al., 2014). A further opportunity may lie in the rising connectivity of even remote smallholder farmers. While accessibility still remains an issue, the rise of new technologies such as mobile phone use for financial services through programs such as M-Pesa could reduce distribution costs (Hess & Hazell, 2013).

2.1.2 Challenges

Empirical literature provides a good snapshot of what some of what the current challenges of index insurance consist of. These micro-level cases focus mostly on smallholder farmer's low take-up of insurance, but also explore the further aspects of index insurance's application such as its technical issues or ecological consequences. An overview of empirical cases beyond the IBLI case are presented in Table 2 and referred to in this section.

The issue of low demand for index insurance product is in many cases related to its cost and the resulting height of premiums that smallholder farmers are not willing or capable to bear. The total cost of index insurance take-up is often not taken into consideration in the design of the product, such as switching cost from informal insurance already in place or the overcoming of trust barriers to the consumers. These factors contribute to an overestimation of demand and the number of smallholder farmers which will be able to purchase index insurance (Binswanger-Mkhize, 2012; Tadesse et al., 2015; Smith, 2016). The Fixed cost of index insurance, although considerably lower than other forms of agricultural insurance, remains substantial and high for poorer farmers, who are also the most vulnerable (Smith, 2016). Some authors also note other factors that possibly influence demand, such as previous payouts and household characteristics (Cole, Stein & Tobacman, 2014; Abugri, Amikuzuno & Daadi, 2017). Some solutions have been proposed to the issue of demand, education of customers for example has proven successful in some instances (Patt, Suarez & Hess, 2010; Dercon et al., 2014).

Because of its relatively recent development, index insurance is still plagued my technical designing issues. For one, basis risk can be difficult to manage and minimize, particularly for areas where both climate and individuals vary substantially (Tadesse et al., 2015). This issue of basis risk is linked to the selection of variables to determine the index, data availability and consideration of all factors that determine the final design of the index (Peterson, 2012; Wang et al., 2013). Little literature focuses on the comparison of different index types and their merits such as Makaudze & Miranda (2010) which explore the benefits of rainfall and NDVI-based indices.

Binswanger-Mkhize (2012) questions the benefits of index insurance overall. A variety of different outcomes, for farmers, credit constraints, investment, food security and government intervention in case of natural hazards, are proclaimed to profit from agricultural insurance as shown in economic models. The author argues that no empirical study has proven this. Similarly to this, Smith & Glauber (2012) and others find no or little overall welfare increase from these programs and question the use of subsidies to pay for them particularly when households seem to prefer cash payouts (Leblois et al., 2014; Marenya, Smith & Nkonya, 2014; Ricome et al., 2017). While they acknowledge a vast technical literature regarding demand, different production effects, willingness to pay or premium rates, it remains unclear whether these programs ultimately benefit the customer and/or insurer.

A further substantial issue is the ecological impact of index insurance, as more recently addressed by John et al. (2017). The authors investigate the IBLI case relevant for this paper. and find evidence that the program's scale-up would negatively impact the pastoralist grazing regions even more than drought conditions already do. The prediction is that the expansion of index insurance could increase instability in the long run as index insurance allows the further introduction of livestock beyond the ecological capacity of the region. The underlying argument is that pasture conditions require more time to recover from drought than it takes for insured households to acquire new livestock (John et al., 2017). Another effect of index insurance programs is that it reduces the demand for fertilizer (Farrin, Katie; Murray, 2014). In other words, numerous effects can be attributed to the introduction of index insurance which may only be uncovered when over time.

2.1.3 Theory

The reviewed literature provides less emphasis on the theoretical underpinnings of index insurance demand and outcomes which are considered in this paper. None the less, we briefly address some main theory approaches that guide the two hypothesis.

Chantarat & Mude (2009) consider a pastoral economy and describe two sources of household wealth or assets, comprising livestock and non-livestock wealth, the former is made up of income from non-livestock activities. These assets can be liquidated through consumption or investment. Livestock is at the centre of the pastoralist household and its main source of income.

According to the standard neoclassical model, the insurance decision can be predicted on the basis of key determinants which are assumed to be household-specific characteristics. Risk aversion, credit constraints and the level of income are determined to be key features influencing the decision to purchase a product such as IBLI (Chantarat & Mude, 2009). This research looks at both the empirically verified determinants, such as income level and credit constraints, and other possible determinants such as mobile phone access and local conditions to provide further depth to the analysis of index insurance demand.

Table 2. Empirical Literature Overview

Source	Region	Sample	Insurance Type	Findings	Methods
Patt et al. (2010)	Ethiopia & Malawi	-	index insurance	Understanding of basic insurance concepts is poor and contributes to low demand, role-playing games could help increase understanding and uptake.	Multinomial logit model
Makaudze and Miranda (2010)	Zimbabwe	9 districts	drought index insurance	Normalised difference vegetation index (NDVI) exhibits higher correlation with yield losses than conventional rainfall index.	Summary statistics comparisons
Dercon et al. (2014)	Ethiopia	117 iddirs (>100 members per iddir)	rainfall index insurance	Training of group leaders emphasizing risk-sharing increases index insurance demand	Intention to Treat (ITT) & IV
Farrin & Murrary (2014)	Zambia	4,286 households	weather-based index insurance (simulation)	Index insurance cost reduces disposable household wealth when no pay-out occurs and hereby reduces demand for fertilizer.	pooled double hurdle model
Cole et al. (2014)	India	989 households	rainfall index insurance	Demand is sensitive to pay-out in previous period, with village-wide effects. Payment effects include changes in purchasing decisions.	OLS and IV analysis
Leblois et al. (2014)	Niger	30 households	weather index drought insurance	Benefit of index insurance only exceeds cost in case of high risk aversion.	Utility model, Calibration
Marenya at al. (2014)	Malawi	276 households	index insurance	Preference of cash payments over index insurance contracts by farmers in choice experiments, even when the latter provided higher returns.	Multinomial probit model
Abugri et al. (2017)	Northern Ghana	315 households	crop drought-index insurance	Willingness to pay (WTP) is influenced by several factors: sex, age, education, insurance awareness, payment type, assets, risk levels, income among others.	binary probit model
Ricome et al. (2017)	Senegal	180 households	weather index insurance	Index insurance leads to limited welfare gains for the group of farmers located in the driest areas. Public funds use for index insurance subsidies is not as efficient as other uses.	Baseline study comparisons

The stochastic dominance approach is taken by Jensen et al. (2016), the authors apply expected utility theory to explore the set of choices households make regarding IBLI and find that the decision to insure fails to dominates. The authors warn that risks remain present as they are not completely eliminated by IBLI and suggest further focus on the outcomes of the product as well as necessary caution in assuming financial tools as IBLI always work as planned.

Our second hypothesis addresses this concern by exploring different outcome components of the IBLI product. Supported by Chantarat & Mude's (2009) explanation of the pastoral economy and its elements of assets from income and their liquidation through consumption and investment, this essay focuses on income and consumption outcomes of IBLI.

2.3 Index Insurance for Development?

The political economy perspective also contributes to the debate surrounding effectiveness of index insurance. Peterson (2012) examines how the index insurance tool may introduce other forms of risk and hereby increasing vulnerabilities of smallholder farmers rather than the opposite. The sources of this increased vulnerability are twofold. Firstly, the importance of local context and circumstances for the implementation of index insurance as a climate change adaptation is noted. The attempt to create a scalable technical solution for highly variable local contexts is questionable considering the range of often information risk mitigation strategies already in place. Müller et al. (2017) consider the local context, such as cultural norms and traditions with respect to risk sharing, to be of vital importance for insurance to not backfire.[1] Besides the move away from existing coping strategies, the exposure to previously inexistent risks, such as economic market risk, is concerning. While the financial tool of index insurance to transfer risks to international markets may enable market expansion, it may affect existing risk mitigation instruments and expose smallholder farmers to further risks through linkages with financial markets (Isakson, 2015).

Peterson (2012) notes that previous similar programs providing 'technical fixes' to problems rather than addressing underlying social causes of inability to adapt to climate change created more bad than good. The issue of climate change should be integrated into economic development rather than be seen as separate issues. The 'double exposure' to globalization and climate change consequences is a reality for vulnerable populations (O'Brian & Leichenko, 2000). A recurring argument is that insurance does not address the fundamental issue of increased risk due to climate change (Mileti, 1999). Similarly, as argued by Isakson (2015): "Financial means cannot substitute for the social and ecological foundations of security." Rather, the increasing risks associated with climate change are taken as a pretext for the financialization and commodification of agricultural risk (Isakson, 2015). While some part of this may be to the benefit of smallholder farmers, the overall attempt to include these actors into the global financial markets through these neoliberal market mechanisms ultimately benefits the financial market.[2]

Our next section delves into the specificities of the case chosen to investigate the issues introduced throughout the literature.

[1] "If insurance is to be an appropriate tool for mitigating the impacts of climate change, it needs to be carefully developed with specific local social-ecological contexts and existing risk coping strategies in mind. Otherwise, it is liable to create long-term maladaptive outcomes and undermine the ability of these systems to reduce vulnerability." (Müller et al., 2017)

[2] "These products cannot be understood simply as development interventions for reducing vulnerability or increasing agricultural production, but also as techniques attempting to articulate a particular chain of social and economic relations premised on the creation of financial consumers." (Johnson, 2013).

3 The Index-Based Livestock Insurance Project

This section provides background information for the Index-Based Livestock Insurance (IBLI) project that is the subject of our empirical analysis. We present an overview of the project implementation, the contract, and product design as well as empirical literature focusing on this project.

3.1 Overview

The index-based livestock insurance (IBLI) project insures pastoralists against livestock mortality induced by drought conditions in the arid and semi-arid lands (ASALs) of East Africa. The International Livestock Research Institute (ILRI) in collaboration with Cornell University and numerous local implementing partners first launched the IBLI product in January of 2010 in the Marsabit region of northern Kenya, as seen in Map 1 towards the end of this section. The IBLI product has since been expanded to include more regions in northern Kenya as well as southern Ethiopia's Borana region as of July 2012. The IBLI program has experienced various adjustments since its launch, such as the local partners providing the risk insurance.[3] Further involvement by NGO's such as CARE Kenya, World Vision International or Mercy Corps has also contributed to program changes and adaptation (Mude, 2014). Furthermore, a more recent development is the consideration of a nationwide version of the IBLI program known as 'Kenya Livestock Insurance Program' by the Kenyan Government, for which no concrete decisions have been taken yet.

The ILRI product provides private insurance to smallholder farmers against livestock mortality linked only to drought. The product design exploits the strong correlation between forage availability, which describes the grazing capacity, as indicated by the Normalised Difference Vegetation Index (NDVI) and livestock mortality. The pay-outs received by farmers depend on the livestock mortality level predicted by seasonal forage availability as measured by NDVI. As such, as other forms of index-based insurance, IBLI overcomes the high cost and availability of data used in conventional insurance mechanisms. Furthermore, as described in the literature previously, moral hazard and adverse selection are ruled out as the insured farmer cannot influence the variables on which the index is based on. However, the imperfect correlation between an individual loss experience and the selected index may result in indemnity pay-outs not reflective of that experience. This problem, known as 'basis risk', highlights the necessity of an IBLI product that is designed meticulously to take into account as many factors as possible to minimize this risk and provide a contract that maximizes its value to the insurer and the insured (Jensen, Barrett & Mude, 2015).

3.2 Design

3.2.1 Contract

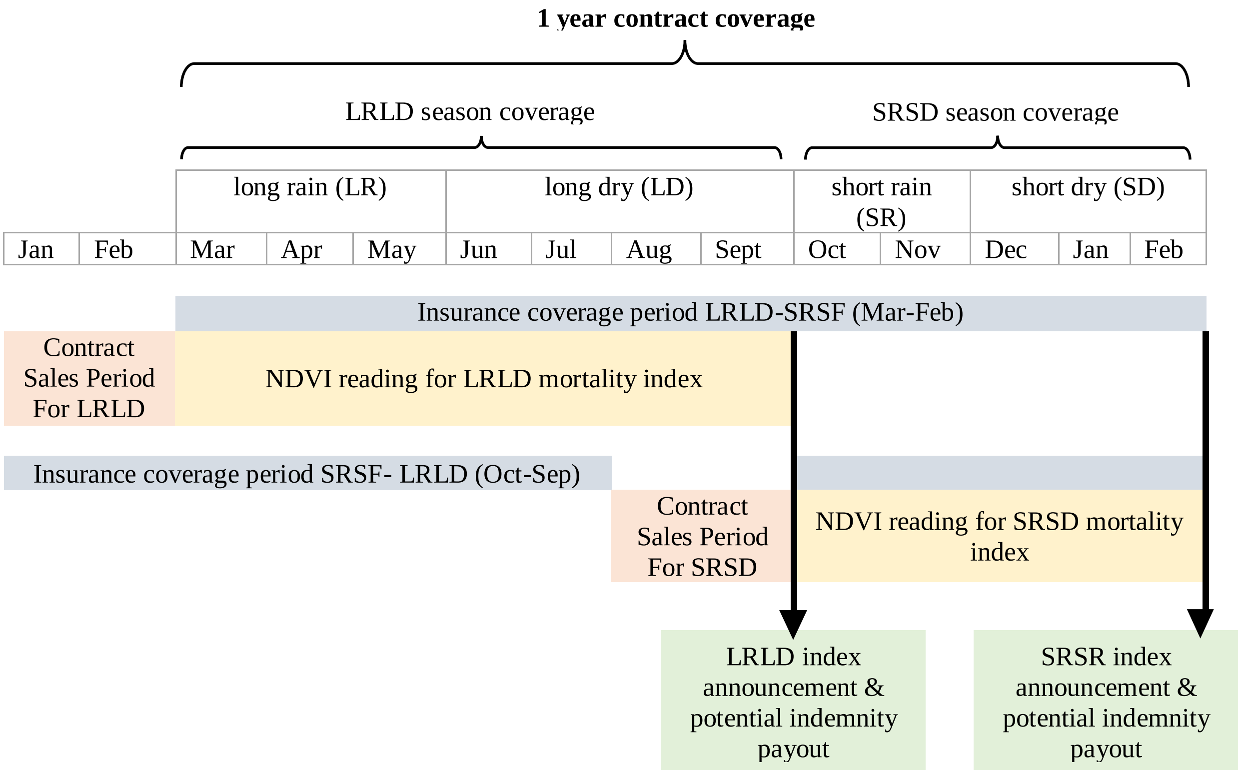
The IBLI contract design is based on the characteristics of the region. Livestock represents a key form of livelihood in the region and is heavily dependent on climatic factors.

[3] Among these local partners are Equity Bank, UAP Insurance Company, APA Insurance Company, and Takaful Insurance of Africa.

The rains are key for forage and water availability necessary for pasture, herders adapt to variation in rains by migrating when possible. The climate in northern Kenya's arid and semi-arid lands experiences bimodal rainfalls. Short rains (October – December) are followed by a short dry period (June – September), this is known as the short-rain-short-dry period (SRSD). This follows the long-rain-long-dry (LRLD) period of long rains (March – May) and long dry season (June – September) (Mude, 2014). The break-down of these seasons as well as the following description of the IBLI contract are illustrated in Figure 1.

The indemnity pay-out is the pay-out the customer receives from the insurance provider if a loss occurs according to the insurance contract terms. For the case of IBLI, this is when the index threshold level is surpassed. The IBLI contract is sold in two periods directly preceding the short-rain and long-rain seasons (in August-September and January-February). The resulting coverage lasts one year and allows indemnity pay-outs after the short-dry and long-dry seasons (March-April and/or October-November). The possibility of coverage overlap exists for March to September and could result in several indemnity pay-outs from the two different contracts, allowing a customer to space out payments and hereby reducing possible financial constraints. For the first three sales periods, the IBLI was sold by UAP Insurance and Equity Bank. From the fourth sales period onwards, APA Insurance sold the insurance and Takaful Insurance of Africa began selling IBLI outside the survey sample in the fifth sales period (Ikegami & Sheahan, 2017).[4]

Figure 1: IBLI contract temporal structure



Created: by Author; Sources: Mude (2009) & Ikegami & Sheahan (2017)

[4] An overview of the dates of the survey rounds, insurance sales and indemnity pay-outs are provided in Appendix Table 1.

3.2.2 Product Design

The two important determinants for the IBLI contract are the value of the indemnity pay-out, based on the estimated loss of livestock units, and the "strike point" or threshold level of the index at which the indemnity pay-out is triggered (Mude et al., 2009). As described in the household survey codebook (Ikegami & Sheahan, 2017), the premium payment (p_h) and indemnity pay-outs (I_h) differ across the five IBLI index areas drawn up in Marsabit in which different factors are likely to affect livestock mortality differently. The overview of the index areas can be found in Map 1. The premium payment (p_h) or cost of insurance for the household is composed of the premium rate for the location-based index insurance area *a* of the household (r_a), the total number of insured tropical livestock units (TLU_h)[5] and the cost associated with the insurance of these livestock units (p_{TLU}), as summarised in the following equation:

Premium payment (p_h):

$$p_h = r_a * TLU_h * p_{TLU}$$

Indemnity pay-out for household h (I_h):

$$I_h = \begin{cases} (i_a - t_h) * TLU_h * p_{TLU} \text{ if } i_a > t_h \\ 0 \text{ otherwise} \end{cases}$$

The second equation above defines the indemnity pay-out for household h (I_h), which is triggered when the predicted livestock mortality for index area a (i_a) exceeds the trigger level of indemnity pay-out for household h (t_h). The pay-out then consists of the difference between this trigger level and the predicted livestock mortality, multiplied by the total number of insured tropical livestock units (TLU_h) and the cost of their insurance (p_{TLU}).

Normalized Difference Vegetation Index (NDVI)

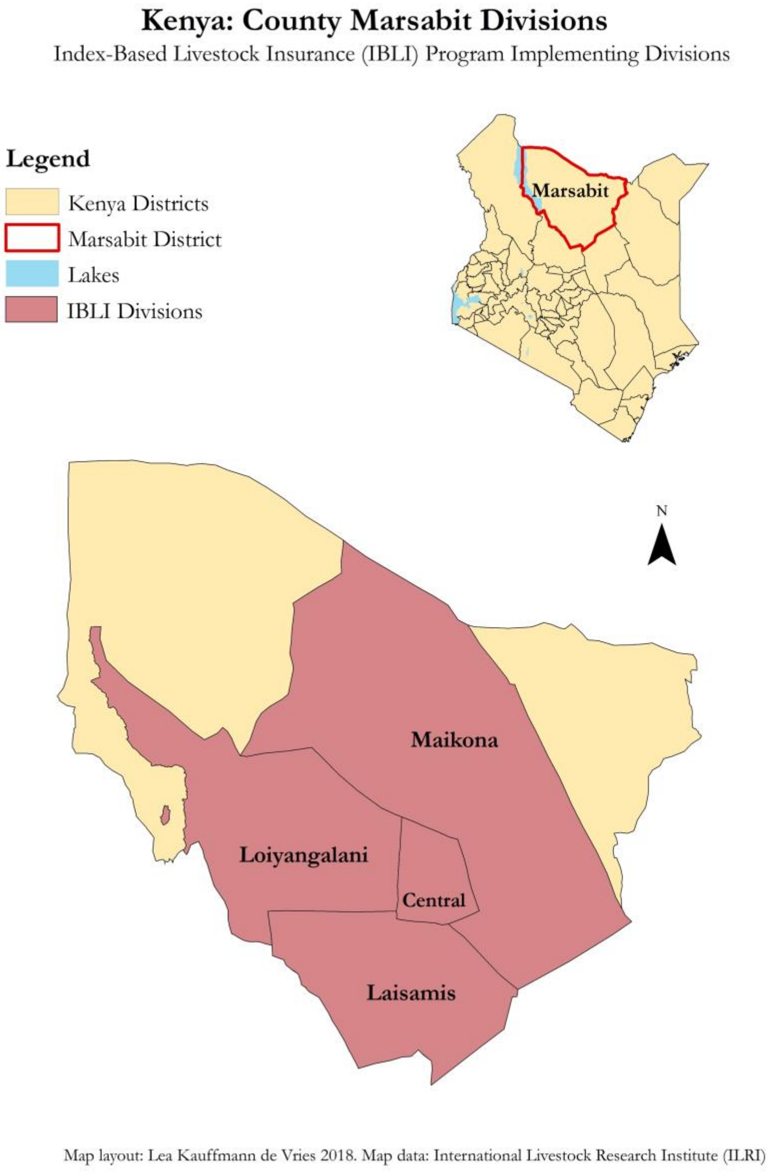
The contract itself is based on a response function that predicts livestock mortality from remotely sensed NDVI data. The Normalised Difference Vegetation Index (NDVI) is based on a difference formula that uses wavelengths (or colours) caused by reflections of near-infrared sunlight on vegetation to compute plant growth density in a certain surface area. NDVI hereby creates a time-series reflecting vegetation density for different applications (Weier & Herring, 2000). The IBLI NDVI data is sourced from the US National Oceanic and Atmospheric Administration (NOAA) satellite's Advanced Very High Resolution Radiometer (AVHRR) and delivers high spatial resolution images in 8km^2 grids. The images are available in 10-day intervals ("dekads") since 1981. The ILRI determines the NDVI series appropriate for each location using information on residence and water points among others.[6]

[5] "The main livestock species in this region are cattle, camel, and smallstock (e.g., goats and sheep). TLU is a standard measure that permits aggregation across species based on similar average metabolic weight. 1 TLU = 1 cow = 0.7 camels = 10 goats or sheep." (Chantarat et al., 2013)

[6] "Because pastoralists routinely graze animals beyond their residential areas, we define the grazing range for each aggregate location—within which NDVI observations are averaged for each period—by identifying the rectangle that encompasses the residential locations and all common animal water points used by herders in that community, plus 0.1 decimal degrees (about 11 km) in each direction." (Chantarat et al., 2013)

The use of NDVI data for index insurance is still limited but has been demonstrated successfully in some applications (Makaudze & Miranda, 2010; Turvey & Mclaurin, 2012; Vrieling et al., 2014). Chantarat et al. (2013) discuss its utility for the prediction of livestock mortality for the IBLI case from both a conceptual and practical perspective. Livestock loss as a result of rainfall is complex, it depends on numerous factors influencing forage availability, water access, predatory pressure and others. The vegetation density and cover reflects this complex interaction and hereby provides a conceptually sound predictor of the livestock mortality. The practicality of NDVI for the IBLI case lies in its availability and cost, as it is real-time data and it is freely available. The limited livestock census surveys for developing regions make the computation of average livestock mortality rates from such sources unrealistic, as is the case for Kenya. Similar issues exist for meteorological data (Chantarat et al., 2013).

Map 1: Index Insurance Areas of IBLI[7]



[7] The two index insurance divisions Central and Gadamoji share an area that could was not separated in the available shapefiles.

3.3 Encouragement Design

Two experimentation components were introduced to the IBLI project for research purposes. Firstly, the so-called ‘knowledge games’ were designed to inform customers about the IBLI product through an educational insurance game highlighting three key lessons. This was done once, between December 2009 and January 2010 (Ikegami & Sheahan, 2017). The second form of encouragement was financial, through coupons discounting the cost of the IBLI product by 10-60 percent. 60 percent of households received such a coupon over the IBLI sales periods and its implementation showed positive effects in uptake (Takahashi et al., 2016). We discuss and control for these encouragement tools in our results.

3.4 IBLI Results

The index insurance project which is the subject of this paper has been subject to different analysis regarding different aspects of the IBLI program.

The project summary provides the methodological background and pricing design of the IBLI product. The authors and project leaders also highlight the major challenges faced during the creation of the IBLI contract, which include the search for high quality data, the design of a good insurance index, the low demand for the product by unfamiliar clients and the cost of delivery of the final product (Mude et al., 2009). A second project launch note further details the issues faced during the first round of insurance sales, which included reflections regarding the sales process of the IBLI insurance and the lack of public awareness of the product which may have dampened uptake (Chantarat et al., 2010).

Overall, the IBLI product is successful in its goal of reducing livestock mortality risk for smallholder farmers, doing so by 25-40 percent as estimated by Chantarat et al. (2009). However, a more recent investigation finds that even though the IBLI product reduces risk losses faced due to covariate risks, households remain exposed to idiosyncratic risks. As a result, households with IBLI insurance maintain a high level of risk. Therefore, although the IBLI program is successful in mitigating some of the risks households face, its applicability as a mitigation tool is questioned by the authors (Jensen, Barrett & Mude, 2016).

As mentioned previously, a reoccurring and concerning issue hampering the success of index insurance is its low demand. It is unsurprising that one of the first empirical investigations into the IBLI program focused on pastoralist’s willingness to pay (WTP) for such a product (Chantarat & Mude, 2009). The authors use the first pilot sale to construct aggregate demand for the product using WTPs and observe the demand to be influenced by existing coping mechanisms and the household’s predictions of livestock loss.

Other findings regarding demand find it to be positively influenced by households’ location in regions experiencing higher livestock loss and households with lower basis risk. Authors suggest that demand is influenced in the case when weather predictions forecast weather threats (Jensen et al., 2016). Bageant & Barrett (2016) find no convincing evidence regarding gender differences in the demand of IBLI products.

The expansion of the IBLI program to Southern Ethiopia also led to empirical investigations of the product in this regions. Although not entirely the same, the product was designed by the same International Livestock Research Institute (ILRI) but implemented with other local partners in Ethiopia. Similarly, the issue of demand is at the forefront of investigations. Authors disprove that a better knowledge regarding the product necessarily increased uptake, but find evidence that subsidised products implemented through coupons lead to immediate significant and permanent rise in demand of IBLI (Takahashi et al., 2016).

4 Data and Summary Statistics

4.1 Household Panel Data

The data for this research consists of annual longitudinal household survey data collected as part of the project described above, the "Index based livestock insurance (IBLI) for northern Kenya's arid and semi-arid lands: the Marsabit Pilot". The purpose of the product is to protect pastoralists in Marsabit from livestock mortality induced by drought conditions in the region. The survey was conducted by the International Livestock Research Institute ILRI), Cornell University, the University of California Davis BASIS Research Program and Syracuse University together with several local implementing partners, including Equity Bank, UAP Insurance Company, APA Insurance Company, and Takaful Insurance of Africa, among others.

As outlined in Appendix Table 1, the pilot of the IBLI product began in 2010 with a first sales period and was continued for nine consecutive sales periods until 2015. The first round of data collection in household survey form took place in the fall of 2009, with further 5 rounds following until fall of 2015. This data analysis includes the data of these 6 rounds over the timeframe of October-November 2009 to 2015.

The survey contains 41 sections with different questions regarding household information, health, education, livestock information, resilience, expenditure and income, among others.[8] This large quantity of variables required a thorough selection process. Variables were selected on the basis of relevance as well as availability for the different survey rounds. The data processing also included the recoding of numerous variables to combine information and construct binary variables. An overview of the selected and adapted variables relevant for this investigation can be found in Appendix Table 2.

Among the key variables of interest for this research are those describing the use of the IBLI product. For this, we have information of whether a household was insured during the past year through the dummy variable 'insured' (which is 1 for insured households and 0 for uninsured households) and continuous 'insured total livestock units (TLU)' variables which indicates how many TLU a household has insured.[9] Further socioeconomic variables have been selected from the survey that reflect individual household characteristics related to their decision to take up index insurance, such as characteristics of the household head, education levels and location of the households in terms of index area. Additionally, considering the context of this research and interest of how index insurance of livestock helps households overcome livestock loss, we consider numerous variables related to livestock, such as TLU, expenses related to livestock, livestock deaths resulting from a weather shock (drought).

The IBLI survey data is very detailed and broad, allowing room for different research avenues. However, as with any survey, several limitations need to be considered preceding data analysis.

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[8] The entire IBLI data is provided in Stata format in different files. Stata is also the statistical software used for this analysis.

[9] "TLU is a standard measure that permits aggregation across species based on similar average metabolic weight. 1 TLU = 1 cow = 0.7 camels = 10 goats or sheep." (Chantarat et al., 2013)

4.2 Data Diagnostics and Limitations

We first explore how balanced our panel dataset is, which is constructed by several sets of cross-sectional observations over time. In the case of an unbalanced panel, not every unit of observation is observed for every time period, as would be for a balanced panel dataset (Wooldridge, 2009). The dropping out of households for some survey rounds, known as attrition, causes an unbalanced panel and can create selection bias attrition related to factors relevant for our analysis.

A limitation of this survey dataset lies in how attrition was dealt with. As with most surveys, the chance that some households will not be surveyed for all rounds of a survey is high. In order to maintain a sample size of 924 households over time, the surveyors resorted to selecting replacement households for the survey round in which the original household could not be located for during an extended period of time. The replacement households were selected on the basis of the TLU class and sub-location of the original household in order to hopefully capture. Of the 924 households surveyed in round 1 to 4 and 923 and 919 in rounds 5 and 6, respectively, 770 households were interviewed in all survey rounds (Ikegami & Sheahan, 2017). As illustrated in Table 3 below, the level of replacement households reaches its highest in round 6 with 5.66% of the survey sample. The total number of replacement households makes up less than 3% of observations overall. Although this may seem like a negligible number, the non-random selection of replacement households and non-random attrition may cause sampling bias and distort our results. In the following summary statistics, we test whether the differences between the repeat and replacement households are significant enough for us to correct of sample biases in our further analysis.

Table 3. Overview replacement and repeat IBLI survey households

	Survey Round						
	1	**2**	**3**	**4**	**5**	**6**	**Total**
Replacement Household							
Number	0	37	30	27	12	52	158
Percentage	0.00	4.00	3.25	2.92	1.30	5.66	2.85
Repeat Household							
Number	924	887	894	897	911	867	5,380
Percentage	100.00	96.00	96.75	97.08	98.70	94.34	97.15
Total	924	924	924	924	923	919	5,538

Source: Author

A second important consideration is the representativeness of our dataset. The survey data was collected only in the Marsabit county of Kenya, a predominantly pastoralist region. As such, the survey data is expected to represent households in this regions. However, the sample selection during a survey process is often unable to represent all individuals within a population. Due to issues of non-response or other, some households may be over- or under-represented. The larger the survey, the higher the likelihood that it reflects the population well. The IBLI dataset provides a low sample size with 924 households. In order to correct for this, the authors apply the commonly used technique of sampling weights, which attributes a weight to each household in terms of their representation. Households that are over- or under-represented receive lower-or-higher weights, respectively. The calculation of these weights was done using the IBLI team's population and livestock census in the Marsabit region conducted in 2009 (Ikegami & Sheahan 2017). This correction allows us to solve the problem of representation in our analysis by computing representative statistics at the different local levels.

A further relevant limitation of this panel dataset are possible cofounding projects taking place in the same region. Specifically, the Hunger Safety Net Program (HSNP), funded by the UK's Department for International Development (DfID), was operating in the region of Marsabit during the survey collection. This program consists of monthly cash transfers to a specific target group of households in the region. The fear that this program may cofound IBLI results by influencing households in similar ways as the IBLI product or could create jointly alter household behaviour, making it difficult to isolate effects attributed to the IBLI product, affected the design and planning of the survey. Variables capturing households' participation in the HSPN "HSNP transfer" and participation in other programs "other aid" are therefore included in our analysis to control for such confounding influences.

The content and quality of the data are also of concern. A concern general to panel data is the data collection process and the issue of self-reported data. Self-reported data is often biased because questioned households are unable to recall certain events or not precisely, exaggeration or attribution can also increase this self-reported data bias. Unfortunately, there is little to do to control for such biases besides making questions as precise as possible and the sample large enough to capture the most accurate and representative data possible.

Additionally, while the overall quality of the dataset is high, there are some inconsistencies over the panel which limit the possibilities for our desired analysis. Over the six survey rounds, the collectors have changed some of the research questions regarding some topics or failed to report the results of some questions. This has posed a particular challenge for the identification of the dependent variable to capture a households' ability increase resilience to livestock losses to drought. Income was selected as such an outcome variable and household expenditure or assets could have captured other components of a households' adaptability. However, for the variable land ownership of irrigated or non-irrigated land for 3 out of our 5 index areas is only observed in round 1. The variable food expenditure, which represents a possible variable affected by livestock losses, is asked with reference to the households' expenditure of the past 7 days before the time of survey questioning rather than the last time period. The possible expenditure variation due to such drought livestock loss shocks may therefore not be captured. We settle with the variable income and non-food or 'other' expenditures as the dependent variables of our second model.

The lack of availability of further precise outcome variables, unfortunately, reduces the ability of this paper explore the effect of being insured when experiencing animal losses due to drought on different household aspects. The broad terms of adaptation and resilience imply impact on numerous outcomes which cannot all be considered, this is a strong limitation to this dataset and as a result this paper.

4.3 Summary Statistics

We base this description of our summary statistics on two tables, the first of which summarises the mean and standard deviation of the different observed variables by round in Table 4. The second table provides the mean of the variables of interest by insurance status for each round and reports the significance of the corresponding t-tests, found in Appendix Table 3. An overview of all variables and information regarding their grouping as binary, categorical or continuous variables can be found in Appendix Table 2.

Our summary statistics have been divided into different sections describing the household in both Table 4 and Appendix Table 3. The first section summarises the characteristics of the household head. Starting with mean age close to 45 years in round 1 this value increases gradually until 51 in round 6, indicating the same household head is observed for most rounds. The statistics regarding gender, coded as a dummy variables taking on value 1 for male, are consistent with this, reporting 60% male household heads over most rounds. Ethnicity and religion are similarly consistent over the rounds. The observations are out of line for round 2 however, where the dataset lacks observations for gender and only 222 out of 924 are reported. A similar issue for the same round 2 is found in the next section addressing household characteristics, all rounds report average household sizes of 4-6 people with average ages between around 22-24 but for round 2 these figures are 2.25 people and an average age of 9.39, respectively. As we constructed the mean household age variable using the reported household size it is not surprising that this data issue is carried over with similarly low reporting levels as for gender. The origin of this missing survey data is unclear. A possibility to deal with this could be to extrapolate the data between round 1 and 3 to generate the missing variables described in round 2. We do not proceed with this but deal with this in our methodology by running models of different specifications.

The key variable representing the insurance status 'insured' found under the Financial Access & Insurance category in Table 4. As explained earlier, this dummy indicates if a household has been insured by taking on the value 1. In the first survey round IBLI did not provide their insurance product yet, explaining inexistent insured households in round 1. The percentage of households that are insured is high for round 2 and 3 where 24 and 26 percent of survey households hold insurance. For the subsequent rounds, it is much lower, with 9 and 7 percent in rounds 4 and 5 and only 1 percent in the last round 1. This raises the question as to whether this drastic drop in insurance adoption is related to households' experiences from the first rounds of insurance or some other unknown factor.

To explore this further, we consider the continuous 'insured total livestock units (TLU)' variable, from which the insurance dummy was created. This variable gives us the number of insured TLU per household. Interestingly, as their number decreases for the later rounds, the mean number of insured TLU increases for those later rounds. From around insured 2.5 TLU for round 2 and 3, to about 13, 7 and 6 TLU for the subsequent rounds. This indicates that while the number of insured households decreased, the households that did take-up insurance in the later rounds on average insured a larger amount of animals. A possible explanation for this could be that the households selecting insurance in later rounds have different amounts of livestock holdings and hereby also their insured livestock numbers differ. This explanation is not entirely confirmed in Appendix Table 3 where the three wealth classes based on TLU holdings are significantly different by insurance status in 3 of 15 cases, however indicating that TLU class should be taken into account in our methodology.[10]

[10] The TLU class is determined by a household's livestock holdings. The classification consists of three wealth classes: low (<10 TLU), medium (10-20 TLU) and high (>20 TLU) (Ikegami & Sheahan 2017).

Table 4. Summary Statistics by Survey Round (1/2)

	Round 1		Round 2		Round 3		Round 4		Round 5		Round 6	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Household Head												
age	45.34	15.85	43.59	13.28	47.78	16.09	48.72	15.92	49.44	15.47	51.15	14.77
age squared	2307.14	1631.57	2071.95	1363.01	2541.85	1729.35	2626.43	1723.89	2682.95	1681.91	2834.36	1649.61
gender	0.6	0.49	0.15	0.36	0.59	0.49	0.6	0.49	0.62	0.49	0.6	0.49
marital status	0.83	0.37	0.83	0.38	0.84	0.37	0.83	0.38	0.84	0.37	0.83	0.37
ethnicity burji	0.02	0.16	0.02	0.16	0.02	0.16	0.03	0.16	0.03	0.16	0.03	0.16
ethnicity borana	0.09	0.29	0.09	0.29	0.09	0.29	0.09	0.29	0.09	0.29	0.09	0.29
ethnicity rendille	0.34	0.48	0.34	0.47	0.34	0.47	0.34	0.47	0.34	0.47	0.34	0.47
ethnicity samburu	0.12	0.33	0.13	0.33	0.13	0.33	0.13	0.34	0.13	0.34	0.13	0.34
ethnicity turkana	0.17	0.37	0.17	0.37	0.17	0.37	0.17	0.37	0.17	0.37	0.16	0.37
ethnicity gabra	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42
religion	3.13	1.68	3.07	1.69	3.07	1.7	3.07	1.69	3.06	1.69	3.04	1.68
Household												
household size	5.42	2.36	2.25	2.26	5.85	2.29	6.15	2.28	6.21	2.26	6.52	2.34
mean age	22.02	9.62	9.39	12.27	22.94	9.45	23.02	9.24	23.31	9.35	24.27	9.56
mean education	1.44	1.93	1.45	1.92	1.46	1.91	1.47	1.9	1.48	1.9	1.49	1.92
income	42634.77	84656.32	56295.8	117422.95	52104.17	117153.97	71084.76	138142.98	79284.14	128375.2	86288.73	146865.91
other expenditure	23978.9	122103.88	19771.72	23129.25	36731.98	69012.42	48905.71	165003.59	46271.51	109044.55	.	.
received transfers	3100.58	9920.65	5865.84	18590.18	4741.69	9300.56	5438.3	10782.83	6660.81	12723.84	7857.72	14232.51
sent transfers	822.87	2805.14	2632.76	9170.35	3382.32	13037.31	2495.64	6264.12	3813.12	21053.56	3399.08	13511.18
HSNP transfer	0	0	0	0	0.35	0.48	0.31	0.46	0.25	0.43	0.42	0.49
other aid	0.95	0.21	0.93	0.26	0.98	0.13	0.96	0.19	0.87	0.34	0.92	0.27
low TLU class	0.6	0.49	0.6	0.49	0.6	0.49	0.6	0.49	0.6	0.49	0.6	0.49
medium TLU class	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42
high TLU class	0.17	0.37	0.17	0.37	0.17	0.37	0.17	0.37	0.17	0.37	0.17	0.37

Table 4. Summary Statistics by Survey Round (2/2)

	Round 1		Round 2		Round 3		Round 4		Round 5		Round 6	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Livestock												
livestock expenses	3243.17	10396.56	1307.28	4318.62	3636.75	10241.95	2203.16	5723.29	2423.92	5236.87	4221.78	9750.14
owned animals	11.29	17.97	11.21	17.2	7.61	9.35	7.96	9.4	8.49	9.24	7.95	10.79
herded animals	14.49	21.72	13.48	20.48	9.22	12.76	8.28	9.84	8.94	9.98	8.72	15.12
TLU loss	8.79	12.46	2.91	5.39	6.58	10.07	3.1	5.33	1.68	1.95	2.75	4.06
adult TLU loss	6.22	8.88	2.18	4.31	4.28	7.28	2.29	4.26	1.18	1.5	1.84	3.13
droughtloss dummy	0.96	0.21	0.64	0.48	0.91	0.29	0.69	0.46	0.56	0.5	0.83	0.38
drought TLU loss	5.82	9.11	1.14	3.2	4.04	6.92	0.89	2.06	0.39	0.8	1.34	1.99
other TLU loss	2.04	5.07	1.64	3.14	2.45	4.98	2.42	4.59	1.34	1.81	1.43	3.52
Financial Access & Insurance												
bank account	0.05	0.21	0.05	0.21	0.05	0.22	0.07	0.26	0.09	0.29	0.05	0.23
lent	0.25	0.44	0.14	0.34	0.07	0.26	0.09	0.29	0.11	0.31	0.18	0.38
merry-go-round	0.05	0.21	0.06	0.23	0.06	0.24	0.04	0.2	0.04	0.2	0.06	0.24
celluse daily	0.19	0.39	0.2	0.4	0.22	0.41	0.31	0.46	0.31	0.46	0.63	0.48
insured (IBLI)	0	0	0.24	0.43	0.26	0.44	0.09	0.29	0.07	0.26	0.01	0.11
insured animals (IBLI)	.	.	2.55	3.19	2.48	2.92	13.21	55.8	7	29.29	6.27	20.02
insurance cost (IBLI)	.	.	1135.81	1470.83	1220.9	4940.52	994.81	1050.94	1911.86	2536.11	1518.15	3401.48
discount coupon	0.00	0.00	0.57	0.50	0.81	0.39	0.58	0.49	0.91	0.29	0.00	0.00
game	0.00	0.00	0.29	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Index Area												
Central	0.12	0.33	0.12	0.32	0.12	0.32	0.11	0.31	0.11	0.31	0.11	0.31
Gadamoji	0.07	0.25	0.07	0.25	0.06	0.24	0.06	0.24	0.06	0.24	0.06	0.24
Laisamis	0.22	0.42	0.21	0.41	0.21	0.41	0.2	0.4	0.2	0.4	0.2	0.4
Loiyangalani	0.35	0.48	0.34	0.47	0.32	0.47	0.32	0.46	0.3	0.46	0.3	0.46
Maikona	0.24	0.42	0.22	0.41	0.2	0.4	0.2	0.4	0.2	0.4	0.19	0.39

Source: Author

Table 4's Financial Access & Insurance category provides further interesting information regarding the access to financial resources by households. Not many households are formal bank account holders, with only 5 and 9 percent overall rounds holding an account. The participation in more informal merry-go-rounds is even lower, between 5 and 6 percent. However, up to 25 percent of households have lent out money in round 1, clearly indicating that the lack of formal accounts does not mean that households do not partake in financial transactions. Particularly interesting is the considerable rise in daily cell use across households, beginning at 19 percent in round 1 in 2009 and rising to 63 percent by round 6 in 2015. A likely explanation for this is the rise of financial mobile services in Kenya.[11] We can furthermore see that the coupon distribution to households took place between round 2 and round 5, with 50 percent of households receiving coupons in round 2, 80 percent in round 3, 60 percent in round 4 and 90 percent in round 5.

The inclusion of these variables is relevant as they may contribute to a households' ability to respond to the loss of livestock resulting from a drought event.

We explore further differences in summary statistics between insured and uninsured households and present the significance of their mean differences in Appendix Table 3. Overall, it is very difficult to discern a relevant pattern from this table. While there are some significant differences between insured and uninsured households. Most explanatory variables mostly show significant differences for one or two of the rounds, with no round drawing particularly many differences. We can therefore say that is it difficult to see whether there are consistent differences between the group of insured and non-insured households over all rounds were shown. While this may be the case, it is prudent to include the variables which have shown some significant differences in our upcoming analysis to ensure such possible differences are accounted for.

As described above, replacement households consist of less than 3 percent of all observations. This number is relatively low because replacement only takes place for the rounds the original household cannot be reached for the days the survey takers are in their region. The non-random selection of replacement households and non-random attrition may cause sampling bias and distort our results. While it has been shown that relatively low levels of attrition below 5 percent tend to cause minimal bias, we still consider the possible issue to ensure the validity of our model (Schulz & Grimes, 2002).

In the Appendix Table 4 we test for differences between the two groups, replacement and repeat households for rounds 3 to 6.[12] The findings show that for many variables there are no significant differences between the mean variables of the two groups. However, for some very important variables, such as those referring to the number of owned animals and animals lost to drought among others there are significant results. The dummy reflecting whether a household has been exposed to livestock loss due to drought is significantly larger for replacement households. This suggests that the households they replace may have similarly been affected by such a shock, which could have caused their absence in the survey.[13] We take into account this issue in our methodology though different specifications as well as a sample selection correction model in our first model.

[11] The M-Pesa mobile phone-based financial service which allows money transactions became one of the most successful programs of its kind in Kenya (Jack & Suri, 2011).

[12] We exclude round 1 as no replacement households were necessary for that round. We exclude round 2 as the IBLI panel dataset did not record which households were replacement households for this round.

[13] Authors Jensen, Barrett & Mude (2016) also test for attrition and find significant differences in household size, consumption and income from livestock-related activities.

5 Methodology

The purpose of this research is to investigate whether the purchase IBLI product allows smallholder farmers to increase their resilience to climate shocks in the Marsabit county of Kenya. Due to the prevalence of droughts in the regions and their effect on livestock in this predominantly pastoralist region, we are interested in whether index insurance is used by households as a resilience-building tool and whether the product indeed helps households increase their resilience to climate change. The upcoming methodology addresses these two components through the following hypotheses:

1) The loss of livestock due to drought positively affects the likelihood of acquiring the IBLI product.

2) A IBLI insured household does not experience the same income loss and consumption decrease as an uninsured household does when experiencing loss of livestock due to drought.

5.1 Model 1. IBLI Adoption

Our first model aims to determine whether the loss of livestock due to drought increases the likelihood of being a IBLI customer, testing Hypothesis 1. above. Beyond this, our estimations are likely to also inform us of the impact of other observed socioeconomic characteristics on the likelihood of having adopted the IBLI product. The appropriate model for these estimations is the fixed effects logit model. This 'limited dependent variable model' uses the binary dependent variable of a households' insurance status ('insured') to provide estimates regarding the likelihood of adopting either status as influenced by a number of explanatory variables.

We begin by presenting the limited dependent variable model. The latent variable y_{it}^* for household i $(i = 1, \dots, N)$ in round t $(t = 1, \dots, T)$ relates to the time-varying observable x_{it} and unobservable characteristics α_i, as well as the error term ε_{it}:

$$y_{it}^* = x_{it}'\beta + \alpha_i + \varepsilon_{it}$$

We cannot directly observe the latent variable y_{it}^*, but we can determine the binary choice model households make to insure or not insure themselves, such that $y_{it} = 1$ $(y_{it}^* > 0)$ and $y_{it} = 0$ $(y_{it}^* < 0)$, respectively. The incidental parameters problem means that results cannot be estimated consistently for the fixed effects attempting to control for unobservable characteristics α_i.[14] Following Chamberlain (1980), the conditional fixed effects logit solves

[14] "The problems with the fixed effects estimator are statistical, not practical. The estimator relies on T_i increasing for the constant terms to be consistent—in essence, each α_i is estimated with T_i observations. In this setting, not only is T_i fixed, it is also likely to be quite small. As such, the estimators of the constant terms are not consistent (not because they converge to something other than what they are trying to estimate, but because they do not converge at all). There is, as well, a small sample (small T_i) bias in the slope estimators." (Greene, 2008)

this issue and allows for consistent estimates of β by applying conditional maximum likelihood:

$$\Pr(y_{it} = 1) = \frac{\exp(\alpha_i + x_{it}\beta)}{1 + \exp(\alpha_i + x_{it}\beta)}$$

As well as reducing the problems of self-selection and omitted variable bias, the fixed effects logit addresses unobserved heterogeneity by implicitly controlling for them through individual intercepts α_i. However, this advantage comes at the cost of interpretability of results as marginal effects cannot be estimated with this model. The most straightforward interpretation alternative is offered by the odds ratio as follows:

$$\exp(\beta) = \frac{\Pr(y_{it} = 1|x_{it} + 1)}{\Pr(y_{it} = 0|x_{it} + 1)} \Big/ \frac{\Pr(y_{it} = 1|x_{it})}{\Pr(y_{it} = 0|x_{it})}$$

Alternative interpretation methods are not valid when T>2. Further limitations to be taken into account is possible time-varying heterogeneity of households, which cannot be controlled for (Pforr, 2013). Another disadvantage of this model, as with all fixed effects estimates, is that they focus on within-household variation rather than taking into account variations across households as well. Little variation in insurance take-up between rounds for households but large variation across households could result in large standard errors leading to imprecise estimations (Williams, 2017).

We address the issue of sample selection bias through the addition of the Heckman Correction Model as a model specification. This method has previously been applied in the IBLI context to investigate different aspects of demand of the IBLI product (Chantarat & Mude, 2009; Jensen et al., 2016; Takahashi et al., 2016; Bageant & Barrett, 2017).

The Heckman correction model is composed of a two-step approach to correct for possible bias in our sample due to non-random attrition or self-selection. The first step is to estimate a probit model, which in our case predicts the likelihood that a household is part of our sample. We use the probit estimations to compute the inverse Mills ratio, which included in our regressions to control for possible attrition causing sample selection bias. The Heckman Correction Model also enables us to test whether there is indeed selection bias by testing the joint significance statistical difference from zero of the Inverse Mills ratios.

5.2 Model 2. IBLI Impact on Income and Expenditure

Our second hypothesis focuses on how households with insurance cope in comparison to households without insurance. We focus on several different outcome variables, including household income and non-food expenditure, and measure how these are affected by the choice to take up the IBLI product in the event of a drought leading to livestock loss. We use a Difference-in-Difference (DID) Model to isolate this impact:

$$Y = \beta_0 + \beta_1 Drought + \beta_2 Insured + \beta_3 Drought * Insured + \beta_4 X_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

The simple DID model allows us to estimate the impact on outcome variables Y, which in our case represents household income and expenditure. The dummy $Drought$ indicates whether a household experienced livestock loss resulting from drought conditions in the past year, with this being the case the dummy takes on value 1. Similarly, the dummy $Insured$ indicates whether the same household was insured via the IBLI program or not, with being $Insured$ taking on value 1. The different observed household characteristics are represented by the vector X_i. The time-varying and unobservable household characteristics are captured by individual intercept α_i and the time fixed effects for each round by γ_t. Lastly, ε_{it} captures the error term.

The DID (Δ_T) estimator captures the difference in the effect of the loss of livestock due to drought for insurance-holders and non-insurance holders on our dependent variable Y. The DID term stems from the fact that we compute the difference of two other differences, the difference between insurance holders experiencing and not experiencing drought (Δ_1) and non-insurance holders experiencing and not experiencing drought (Δ_2).

1st Difference (Δ_1)

$$E(Y|Insured = 1; Drought = 1) = \beta_0 + \beta_1 + \beta_2 + \beta_3$$

$$E(Y|Insured = 1; Drought = 0) = \beta_0 + \beta_1$$

$$\Delta_1 = \beta_2 + \beta_3$$

2nd Difference (Δ_2)

$$E(Y|Insured = 0; Drought = 1) = \beta_0 + \beta_2$$

$$E(Y|Insured = 0; Drought = 0) = \beta_0$$

$$\Delta_2 = \beta_1$$

Total Difference-in-Difference Δ_T

$$\Delta_T = \beta_3$$

The DID estimator is β_3. Relating back to our hypothesis and research question, β_3 captures whether an insured household experiences the same effects to income and consumption as an uninsured household when experiencing livestock loss due to drought. This relates to our research questions by indicating whether the IBLI product is a feasible adaptation tool or not.

The DID technique requires several data assumptions, such as the parallel trend assumption and is the hardest to fulfill. The parallel trend assumption stipulated that in the absence of our treatment, the IBLI program, there is no difference between the group taking on the insurance and those not taking up the insurance is the same in the case of a drought event. When the effect of a treatment over time is measured, rather than coinciding with a drought event as for our case. The differences between the two groups for each round were inspected in the data section with the corresponding Appendix Table 3 that showed some significant differences between groups for some variables in certain rounds. However, no consistent differences between the group of insured and non-insured households over all rounds were shown.

A further critical assumption is that of exogeneity of our explanatory variables of interest, insurance status and drought experience. To fulfill this requirement these variables should not be endogenous, i.e. correlated with the error term (ε_{it}). For the explanatory variable indicating livestock loss due to drought conditions, we briefly test for exogeneity by regressing the drought outcome to other household explanatory variables. We expect that no explanatory factors significantly influence the likelihood of experiencing drought conditions. Appendix Table 5 indicates that this is indeed the case and we can carefully assume drought livestock loss is an exogenous shock.

While drought is subject to external weather conditions and therefore intuitively exogenous, insurance take-up is not. Whether a household decides to acquire IBLI insurance can be influenced by numerous different household characteristics. Our model makes an effort to control for these characteristics through a range of control variables capturing observable household characteristics (X_{it}) as well as unobservable household characteristics through household fixed effects (α_i). Beyond including fixed effects at the household level, we also control for time fixed effects by round (γ_t) and cluster standard errors at the index insurance district dimension to allow for correlation between observations at these location levels.[15]

However, the possibility that unobserved household characteristics, such as the risk adversity of a household, still influence its decision whether to take-up the insurance remain. For this reason, a further specification to our model is the inclusion of interaction variables between household characteristics and the dummy for drought loss, with the corresponding coefficient (β_5) as seen in the equation below.

$$Y = \beta_0 + \beta_1 Drought + \beta_2 Insured + \beta_3 Drought * Insured + \beta_4 X_{it} \\ + \beta_5 X_{it} * Drought + \alpha_i + \gamma_t + \varepsilon_{it}$$

The inclusion of these variables attempts to capture household differences in response to drought effects and hereby control for factors that could influence insurance take-up. The possibility that the insurance remains an endogenous variable cannot be completely excluded and results should therefore be considered with care. Further alternatives to control for such biases include the use of instrumental variables to isolate the exogenous component in our variable of interest and hereby its impact on our outcome variable of income or expenditure. Identifying such an instrument requires a strong first stage, which describes the correlation between the possible instrumental variable and the insurance dummy. Unfortunately, such an instrument could not be identified for this dataset which would have been an added benefit to this analysis.

[15] The five index insurance districts include Maikona, Central, Gadamoji, Laisamis and Loiyangalani.

6 Results and Discussion

In this section, the results are presented and discussed. We begin by considering which and why household characteristics influence the IBLI product take-up. We continue with our second model focusing on whether how the IBLI product affects a household's income and consumption levels in the event of drought-induced livestock loss.

The findings from both models are discussed, related to previous findings presented in the literature review and brought into the context of our research question. We conclude each section by outlining some major limitations to our results.

6.1 IBLI Adoption

We apply the fixed effects logit model to investigate how the different household characteristics contribute to the decision to take up insurance. The first hypothesis states that the loss of livestock resulting from drought positively contributes to the acquisition of index insurance in this case. The results are displayed in Table 5 under several different models representing varying model specification. Some specification are applied to all models: time fixed effects by rounds, households fixed effects and robust and division clustered standard errors.[16] The dependent variable for all models is the insurance status dummy of the household (i.e. whether the household was insured via IBLI or not).

All results are displayed in the computed odds ratio metric; the standard errors are reported in brackets below the odds ratio. The logit model does not provide easily interpretable coefficients. The transformation of those coefficients into odds ratios to facilitate interpretation is therefore common. The interpretation is as follows. For example, in (1) we can see that the odds ratio for marital status is 1.165. This suggests that for a household with a married head the odds of being insured is 1.165 times higher than for a household that does not have a married household head. In other words, being married positively influences the level of IBLI adoption if this estimate were significant.

The first and second column display our first two Models, (1&2). The difference between the two models, as is the difference between (3&4), is the exclusion of round 1 and 2 of our sample for Model (2). This has to do with some of the limitations to the dataset in these two rounds, with IBLI only having been implemented in the 2nd round which also does not provide information with regard to which households are replacement households. The information on replacement households is used in Model (3&4) which use the Heckman Correction Model to correct for possible sample selection biases, as explained in the methodology. The exclusion of round 1 and 2 is for comparative purposes and also aids to check the robustness of our model. We additionally test and report whether the inverse Mill ratios estimated are jointly significantly different from zero, which means that we reject the null hypothesis and that that sample selection bias is present in our sample, most likely cause by non-random attrition or replacement as described in previous sections.

Focusing on the differences between Model (1&2) and the last two Models (3&4) we can see that there are no considerable contrasts between the two. Overall, the different specifications do not seem to give rise to different results with exception of the impact of a

[16] Robust standard errors correct for heteroscedasticity, that cannot be tested for with the logit model, and clustered standard errors correct for correlation of observations within groups. The clustering level chosen for our case reflects the index areas or divisions which define different location-based characteristics included in the insurance contract specifications and the possible common exposure to drought and resulting livestock loss by households.

household's classification into the wealthiest third of the sample in terms of total livestock units (TLU). This shows to increase the odds of adopting the IBLI product by 1.389 when compared to a household in the lowest TLU class, a result only significant for Model (1). A first observation is that most results are very close across models, this could highlight the strength of our model and identification or suggest the need for further robustness checks.

We begin by considering the household head characteristics and their possible contributions to IBLI adoption as estimated in our model. The household head is an important decision maker regarding a household's decision to adopt insurance and his or her characteristics could possibly impact such a decision.

Age is the first household head characteristic and provides a significant estimate for (3). Model (3) and (4) predict that the odds of adopting the IBLI product decrease in odds by 0.995 for each additional year of the household head. This confirms a similar finding by Bageant & Barrett (2016) who found a minor negative association between age and the decision to purchase IBLI in Southern Ethiopia. A case study on index insurance in Northern Ghana also found a negative effect of age on farmer's willingness to pay (Abugri, Amikuzuno & Daadi, 2017). A possible explanation for these results is that younger household heads are more willing to try out new methods or, as suggested by Abugri et al. (2017), that younger farmers larger have planning horizon, which increases their incentives to invest in new technologies. Age could also be related to other characteristics, such as education or number of children that could influence this outcome.

For gender, for which the dummy variable is equal to 1 for men, we find a non-significant negative impact on IBLI adoption for male-headed households. While the disproportionate impact of climate shocks on women would suggest a higher IBLI uptake, our results confirm other findings of a limited gender effect despite this (Bageant & Barrett, 2016). Similarly, the expected positive impact of mean education, which denotes the average level of education in the household, does not seem to significantly contribute to IBLI adoption as expected. Rather, we find a negative odds ration across all coefficients predicting that odds decrease by 0.962 for Model (3) for each additional year in a household's mean schooling. Takahashi et al., (2016) find a different result for the IBLI case when looking at just the household head's education level, finding that it contributes positively. This could confirm the idea that the household head as the main decision maker. The marital status of the same shows no significance or clear direction of how it affects IBLI adoption.

Interestingly, household size and income are both not significant, with income even showing almost no effect on a household's choice to purchase the IBLI product. Livestock expenses and the number of owned TLU, total livestock units, of a household equally show next to no discernible impact. Although these variables are not thoroughly discussed in the literature, their results lend support to the ambiguity concerning household's reasons for IBLI and general insurance uptake. With exception of income, that is suggested to reduce demand as it reflects livelihood sources from outside agriculture (Chantarat & Mude, 2009).

Moving to the variables reflecting the simple loss of any and the unit amount of livestock loss to drought by the drought loss dummy variable and drought TLU loss variable, respectively. We find the ratio reflecting the impact of the number of animals lost to be very low, only increasing odds for insurance take-up by 1.001 in (3) per total livestock unit on average. The loss dummy shows a somewhat larger negative impact with a 0.935 reduction in IBLI adoption odds. While both results are not significant, the simple loss of animals to drought, rather than the amount of animals lost to drought, seems to carry a relatively greater impact on insurance take-up. It should be noted that since these losses are compared against IBLI take-up in the same year, loss can maybe not be expected to influence take up.

Table 5. IBLI Adoption

	(1)	(2)	(3)	(4)
age	0.995	0.995	0.995*	0.995
	(-1.07)	(-1.85)	(-2.07)	(-1.91)
sex	0.857	0.856	0.892	0.898
	(-0.86)	(-1.13)	(-0.61)	(-0.55)
marital status	1.065	1.037	1.003	0.968
	(0.26)	(0.18)	(0.01)	(-0.11)
household size	1.037	1.036	1.048	1.048
	(1.24)	(1.08)	(1.63)	(1.56)
mean education	0.964	0.971	0.962	0.969
	(-0.86)	(-0.59)	(-0.80)	(-0.62)
income	1.000	1.000	1.000	1.000
	(0.38)	(0.01)	(0.56)	(-0.27)
livestock expenses	1.000	1.000	1.000	1.000
	(0.94)	(1.07)	(0.92)	(0.95)
owned animals	1.009	1.011	1.010	1.011
	(1.57)	(1.09)	(1.06)	(1.13)
drought loss	0.927	0.902	0.926	0.899
	(-0.48)	(-0.98)	(-0.77)	(-0.97)
drought TLU loss	1.000	1.001	1.000	1.000
	(0.02)	(0.07)	(-0.04)	(0.01)
game	1	1	1	1
	(.)	(.)	(.)	(.)
discount coupon	2.534***	2.536***	2.522***	2.521***
	(4.68)	(4.65)	(4.87)	(4.83)
HSNP transfer	1.072	1.081	1.064	1.072
	(0.43)	(0.31)	(0.23)	(0.26)
bank account	0.834	0.841	0.720	0.722
	(-0.68)	(-0.47)	(-0.92)	(-0.87)
merry-go-round	1.118	1.093	1.004	0.973
	(0.41)	(0.22)	(0.01)	(-0.07)
cell use daily	2.024***	2.029***	1.981***	1.981***
	(3.98)	(8.50)	(6.87)	(6.44)
Wealth TLU				
M TLU class	1.121	1.144	1.133	1.155
	(0.70)	(1.24)	(1.16)	(1.35)
H TLU class	1.389*	1.413	1.396	1.420
	(1.99)	(1.31)	(1.25)	(1.33)
Specifications				
Ethnicity Control	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes
Heckman Correction			Yes	Yes
F-Test IM Prob>Chi2			0.000	0.000
N	2749	3592	2749	3592

However, previous IBLI literature has noted that demand is influenced by forecast predictions of weather threats (Jensen et al., 2016).

The variables addressing some of the IBLI program implementation strategies are coupons and games, described in the previous IBLI and data section. The lack of implementation of the game provides unsurprising results in our models. While only 266 households participated in the game in round 1, almost 50% of households received a coupon of some sort. Games show to have no impact on the level of IBLI adoption while coupons show to significantly increase odds by 2.522 in model (3). These results are in line with findings from the IBLI implementation in Ethiopia, where the knowledge games showed did not affect uptake but coupons lead to immediate significant rises in IBLI product uptake (Takahashi et al., 2016). The finding that coupons more than double the odds of IBLI uptake through a reduction of the cost of the product aligns with the high price elasticity of demand of the poorest households (Chantarat & Mude, 2009). This finding suggests that the lack of demand mainly stems from the cost or otherwise low incentives of households to buy IBLI.

Lastly, we address the variables describing household's financial tools. Beginning with HSNP transfers, the targeted cash transfer Hunger Safety Net Program (HSNP), that seem to positively influence a households' odds to adopt the IBLI product by 1.072 in model 4. Since HSNP was not recorded for the first two rounds, model (2&4) would provide the accurate odds ratio of its influence. This result is insignificant, none the less, the positive sign could be a reflection of a household's connection to governmental initiatives which may relate to its willingness to take up the IBLI program.

The merry-go-round and bank account variables represent similar forms of financial access, one rather informal and the other formal that show positive and negative insignificant odds of IBLI take up, respectively. We should note that the relatively low take-up of these instruments, with the summary statistics noting only 5% of the sample to hold bank accounts and similarly with merry-go-rounds, makes these a variables less important household determinant of take up. Cell use, on the other hand, is, next to discount coupons, the only odds ratio significant across all our specifications, indicating that daily cell almost double the odds of taking up IBLI by increasing them by 98 percent in Models 3 & 4. As mentioned in the data section, there is an overwhelming rise in daily cell use over the rounds beginning at 19 percent and rising to 63 percent. This, as well as our results, suggest a rising importance in connectivity for households in Marsabit and its positive impact on their take-up of insurance and possibly other financial tools. This could be linked to the rise of financial services through the introduction of mobile money services such as M-Pesa, which has opened households' pathways to other financial services such as insurance through the IBLI product. This angle deserves further attention in connection with the literature focusing on the rise of mobile financial services in Kenya (Jack & Suri, 2011).

Overall, we do not find enough evidence to reject the null hypothesis that the loss of livestock resulting from drought positively contributes to IBLI adoption. Although the odds ratio of the drought loss dummy does unexpectedly suggest a negative association. Different household expectations could influence this. Considering the limitations of our animal drought loss variables in terms of summarizing information for two insurance purchase periods and the aggregation of loss over the past year before the survey, a rather inconclusive result should maybe not be surprising. An interesting exploration to pursue this question further could be the seasonal breakdown of the data as well as the inclusion of externally determined drought shocks to the different index area. This suggestion would also address our concern of exogeneity. A further exploration could look at the time dimension, such as the possible lag effect of the shock on adoption of the IBLI product in the following period.

6.2 IBLI Impact on Income and Expenditure

Our second hypothesis states that households that have purchased the IBLI product will not be as negatively affected by the loss of livestock due to drought as an uninsured household would. This negative effect is measured by two different outcomes that provide the two dependent variables for our model, expenditure and non-food or 'other' consumption. In other words, the IBLI product is expected to positively affect the outcomes of those two variables in the case of livestock loss occurrences due to drought. The Difference-in-Difference (DID) Model introduced in the methodology section estimates this impact through the DID estimator, in our model this estimator is the interaction variable of insurance and animal loss due to drought (DID estimator = insurance*droughtloss). A number of household characteristics control for other variations in our dependent variables.

Differently from our previous model, the figures reported in the tables are coefficients and do not have to be interpreted as odds ratios but following the common rules with a dependent variable in logarithm form.[17] Our specifications to all models include time fixed effects using the survey rounds as well as robust standard errors clustered at the index area location level. We focus on Table 6 and Table 7 which present the regression results using log income and log other consumption as dependent variables, respectively. Both tables present models with the same specifications. Models (1) and (2) that do not control for the TLU class of households and (2) and (4) exclude rounds 1 and 2 as done in our previous hypothesis testing due to some data issues with these rounds.[18]

Robustness checks are performed in Appendix Table 7 and 8, which we will refer to briefly throughout our results discussion. A further robustness check includes interaction variables between all considered household characteristics and the droughtloss dummy, reported in Table 8.[19] With this interaction, we attempt to further control for possible variations in our dependent variable resulting from changes in household characteristics linked to the condition of livestock loss due to drought.

6.2.1 Income

We begin our results description by focusing on the first dependent variable, ln of income in Table 6. Already the first variable, the dummy of drought loss presents an odd result. For the unrestricted Model (1&3), the coefficient has a positive sign, indicating animal loss to drought has a positive albeit minor impact on income. However, this coefficient is small and not significant. The coefficient of our insurance dummy suggests households that are insured on average report a higher income than those that are not. A possible explanation for this is that the IBLI provides benefits beyond its payout during drought conditions, such as the ability of the household to focus on its most productive aspect, livestock, without having to diversify income streams to reduce risk (Hess & Hazell, 2013).

[17] Since our dependent variables are in logarithms, the interpretation of coefficients is as follows: the change of an explanatory variable, such as insurance from 0 to 1, produces a percentage change in income of 100*coefficient estimate. In other words, coefficients multiplied by 100 provide the percentage estimate in a change of the dependent variable. For the example of drought loss in Model (1), a household that experiences drought loss observes an average income 2.4 percent higher than a household that does not experience animal loss to drought.

[18] The inclusion of many explanatory variables increases the likelihood of collinearity which affects the ability to estimate the coefficients. Stata automatically omits included variables that display collinearity. For all DID models the omitted variables due to collinearity by Stata include: marital status, mean education and ethnicity controls.

[19] The control variables bank account, merry-go-round and cell use daily have been hidden for Table 9 model (1) as it was omitted for all other models in the table. None of the variables are significant.

Table 6. IBLI Impact on LN Income

	(1)	(2)	(3)	(4)
drought loss	0.024	-0.004	0.023	-0.002
	(0.26)	(-0.07)	(0.25)	(-0.04)
insured (IBLI)	0.140	0.120	0.137	0.121
	(0.69)	(0.69)	(0.67)	(0.70)
insurance*droughtloss	-0.182	-0.120	-0.187	-0.126
	(-0.85)	(-0.56)	(-0.87)	(-0.59)
age	0.007**	0.003	0.007**	0.003
	(5.57)	(0.62)	(5.59)	(0.60)
sex	-0.0110	0.102	-0.0136	0.101
	(-0.06)	(0.66)	(-0.07)	(0.65)
household size	0.0873**	0.107*	0.0914**	0.111**
	(4.50)	(3.96)	(5.22)	(4.62)
livestock expenses	0.000	0.000	0.000	0.000
	(2.23)	(0.86)	(2.24)	(0.87)
owned animals	0.0126*	0.0178*	0.0125*	0.0176*
	(3.03)	(3.77)	(3.03)	(3.69)
discount coupon	-0.015	-0.037	-0.012	-0.034
	(-0.46)	(-0.70)	(-0.35)	(-0.64)
HSNP transfer	-0.111	-0.112	-0.114	-0.115
	(-1.83)	(-1.55)	(-1.98)	(-1.63)
bank account	0.285*	0.218	0.284*	0.218
	(3.19)	(2.35)	(3.20)	(2.37)
merry-go-round	0.003	-0.022	-0.000	-0.025
	(0.05)	(-0.58)	(-0.00)	(-0.64)
cell use daily	0.139*	0.143	0.135*	0.140
	(3.27)	(1.86)	(3.19)	(1.84)
Wealth TLU				
M			-0.107**	0.0378
			(-4.21)	(1.24)
H			-1.318***	-1.040***
			(-31.01)	(-18.57)
Constant	8.705***	9.078***	8.928***	9.219***
	(41.89)	(32.02)	(44.56)	(33.76)
Specifications				
Division Clustering	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes
N	4210	3368	4210	3368

robust standard error clustered at index area level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our main variable of interest representing the DID estimator is the interaction variable between insurance and drought loss, which estimates the impact of IBLI purchase when the households experience loss of livestock due to drought. Interestingly, the DID coefficient estimator provides a negative estimate. Although it is not significant and therefore should be interpreted with care, this result suggests that in the case of drought and resulting livestock loss, an insured household's income is estimated to be 18 percent lower than for a non-insured household for Model (1&3). This suggests that the IBLI product does not allow households to avert the negative impacts of a livestock loss due to drought on income. However, the DID coefficients are not significant and our hypothesis can therefore not categorically by rejected. Appendix Table 7 includes further specifications and robustness test, the DID estimator only becomes negatively significant in the case that the insurance dummy is replaced by the continuous variables denoting the number of insured total livestock units (TLU) and the sample excludes rounds 1 and 2. These specifications are useful to check whether the signs of our coefficients remain consistent as possible biases may influence outcomes. This sign is also robust to the introduction of interactions of household characteristics with the drought loss dummy in Table 8. We discuss this finding of the DID estimator further below.

For the other control variables included in our Models there also are not many significant results, except for household size, owned animals, bank account and daily cell use coefficients are significant, indicating that these variables influence income. However, the introduction of our drought loss interactions in Table 8 reduce the significant control variables, consistent across (1) and (2) to household size and HSNP transfer. Indicating that one extra household member increases total income by about 8-10 percent. This could be due to the increased labor and therefore income capacity an additional member adds to the household. The significant and rather large negative impact of the HSNP transfer of 25 percent on income in Table 8 makes sense, since the conditions of the transfer are based on household characteristics including how poor they are, as it is a social protection program (Mude et al., 2009). A possible further reason for the size of the coefficient could be that it captures household conditions not included in other explanatory variables, although this would mean that other coefficients could be biased.

6.2.2 Non-Food Consumption

We continue with our second dependent variable which is the ln of non-food or other consumption in Table 7. The coefficients of the droughtloss dummy, insurance status and our DID estimator are very similar to the results for income. Similarly, the two dummy variables are positive, with the loss of animals because of drought showing a small somewhat larger 7 percent impact on income on other consumption than income for Model (1). The coefficient of our insurance dummy suggests households that are insured on average report a higher income by 22 percent in Model (1) than households that are not IBLI insured. As explained for our income dependent variables, the level of consumption could positively be impacted by the benefits of insurance beyond its payout activities. A household might possibly consume more as the knowledge of being insured allows them to reduce other activities dedicated to risk management. This is in line with the risk ranking exercise done by Chantarat & Mude (2009) who found a reduction of consumption to be among the existing coping strategies for households against weather shocks such as drought. Less need for risk coping strategies through IBLI would then allow increased consumption to take place.

Moving to the DID coefficient, our real variable of interest, the estimation is negative and not signification. This result, similarly to our result for income, suggests an insured household's consumption is estimated to be 15 percent lower than for a non-insured

Table 7. IBLI Impact on LN Other Consumption

	(1)	(2)	(3)	(4)
droughtloss dummy	0.0692	0.0151	0.0699	0.0171
	(1.00)	(0.22)	(1.01)	(0.25)
insured (IBLI)	0.222	0.181	0.222	0.181
	(1.67)	(1.54)	(1.66)	(1.55)
insurance*droughtloss	-0.151	-0.134	-0.156	-0.142
	(-1.35)	(-1.04)	(-1.44)	(-1.15)
age	0.00109	-0.00394	0.00104	-0.00405
	(0.30)	(-0.58)	(0.29)	(-0.60)
sex	0.321	0.148	0.318	0.143
	(1.75)	(0.50)	(1.73)	(0.48)
household size	0.0611	0.0804	0.0645	0.0868*
	(1.85)	(2.20)	(2.09)	(2.86)
income	0.000	0.000	0.000	0.000
	(1.91)	(1.81)	(2.21)	(2.46)
livestock expenses	0.000	0.000	0.000	0.000
	(2.36)	(2.07)	(2.35)	(2.06)
owned animals	0.00450**	0.0172***	0.00449**	0.0170***
	(4.75)	(19.95)	(4.76)	(19.55)
discount coupon	0.0537	0.0496	0.0568	0.0535
	(0.81)	(0.65)	(0.87)	(0.71)
HSNP transfer	-0.255*	-0.0705	-0.256*	-0.0705
	(-3.71)	(-2.39)	(-3.74)	(-2.42)
bank account	0.0462	0.133	0.0426	0.128
	(0.59)	(1.57)	(0.53)	(1.46)
merry-go-round	0.384*	0.481*	0.385*	0.484*
	(2.60)	(3.66)	(2.61)	(3.69)
cell use daily	0.0824*	0.109*	0.0784*	0.105*
	(3.09)	(3.12)	(2.92)	(2.85)
Wealth TLU				
M			-0.0143	0.0263
			(-0.66)	(0.74)
H			-0.929***	-1.309***
			(-13.04)	(-18.75)
Constant	8.464***	9.274***	8.603***	9.448***
	(36.21)	(26.41)	(39.86)	(30.57)
Specifications				
Division Clustering	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes
N	3611	2693	3611	2693

robust standard error clustered at index area level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

household for Model (1&3) when the household experiences a drought and resulting livestock loss. This result is not in line with our hypothesis, for which we stated that we expect consumption of IBLI holding households not to experience the negative effects as non-insured households in the case of drought loss occurrences. Appendix Table 8 displays difference model specifications over which our described results are robust to, with exception of Model (7) and (9) for which we estimate a positive DID coefficient when we exclude the insured dummy. This estimate is much lower, displaying an 8 percent increase in consumption for insured households experiencing loss of animals to drought. Our other robustness check using interaction variables Table 8 also estimates negative coefficients for our DID.

The further control variables included our regressions on consumption are the same as those for total income with the exception that income has been added as an explanatory variable for the consumption models. In Table 7 we can see that the only variables that enter significantly and positively are owned animals, merry-go-rounds, daily cell use over all four models and household size for Model (4). HSNP transfers coefficients enter significantly negatively for our unrestricted sample. Our robustness checks in Table 8 reinforces the positive role of household size for consumption as with income, this makes sense since a larger household consumes more. The other previously significant explanatory variables lose significance with these specifications in Model (3&4) with the last three being excluded due to collinearity.

6.2.3 Discussion

Overall, our findings paint a more complex image of the interaction between income or consumption and livestock losses to drought and IBLI uptake than initially assumed through our hypothesis. The result could indeed indicate that the IBLI product does not positively impact household's income or consumption in the long run. There is some support in the literature for this as were described in the disadvantages of index insurance of our literature review, the lack of recorded welfare increases by similar programs (Smith & Glauber, 2012), the possibility of increased risk exposure to other types of risk including financial risk (Peterson, 2012; Isakson, 2015) and the increased ecological vulnerability of regions with insurance (John et al., 2017). The overall lack of evidence of positive impacts from index insurance programs have also been noted (Binswanger-Mkhize, 2012). These rather negative takes on index insurance indicate that the take-up may indeed cause negative effects. More importantly, with relevance to our research question regarding the adaptability of smallholder farmers to climate shocks such as droughts, index insurance may be a short-term coping mechanism but not address long-run adaptability of households which goes beyond short-term financial pay-outs through products such as IBLI.

Our conclusion needs to take into account limitations concerning our dependent variables. Firstly, the limitation of two dependent variables is severe for answering a question regarding a households' ability to cope with the impact of drought, which has many different effects. A second limitation to these variables relates to the more technical aspects related to the disadvantages of self-reported data and difficulties of quantifying amounts for income and consumption that are informal and follow seasonal patterns.

The income variable can be derived from something else than livestock, meaning that variations in income are not necessarily due to loss of livestock from drought. Livestock, as noted by Bageant & Barrett (2016), is a productive asset holding of households in this regions and their predominant source of income, meaning other forms of income do exist that can reduce the impact of livestock loss due to drought, which would not be influenced by the IBLI product. Equally, non-food consumption is composed of multiple components which Chantarat, Mude & Barrett (2009) have noted to possibly include consumption of other types informal insurance or other payments. Previous literature also found that the IBLI product only decreases a minimal amount of the total risks households face (Chantarat, Mude & Barrett, 2009; Jensen, Barrett & Mude, 2016). If income is a source of wealth and consumption a way to liquidate income and assets we would expect similar impacts on both variables as we measured, this has indeed been confirmed with our model but our hypothesis of their positive impact has not.

Table 8. IBLI Impact on LN Income and LN Consumption with Drought Loss Interactions

	Ln total income		Ln other consumption	
	(1)	(2)	(3)	(4)
droughtloss dummy	-0.326	-0.0810	0.370	0.548
	(-0.69)	(-0.18)	(1.94)	(1.43)
insured (IBLI)	0.323	0.318	0.275	0.263
	(1.27)	(1.22)	(1.34)	(0.95)
insurance*droughtloss	-0.457	-0.525	-0.173	-0.254
	(-2.30)	(-1.98)	(-1.18)	(-1.52)
age	0.00150	0.00823	-0.00199	-0.00870
	(0.26)	(0.80)	(-0.25)	(-1.18)
sex	-0.160	-0.238	0.384	0.320
	(-0.73)	(-0.94)	(1.60)	(1.49)
household size	0.0974*	0.0810*	0.157**	0.145**
	(2.94)	(3.69)	(4.40)	(4.89)
income			0.000	0.000*
			(2.07)	(3.00)
livestock expenses	-0.000	-0.000	0.000*	0.000
	(-0.39)	(-0.76)	(2.78)	(2.45)
owned animals	0.0160*	0.0163*	0.00482	0.0115
	(3.91)	(3.57)	(0.80)	(1.24)
discount coupon	-0.203	-0.188*	0.0698	0.113
	(-2.46)	(-3.91)	(0.45)	(1.22)
received transfers	-0.000	-0.000	0.000	0.000
	(-0.59)	(-0.78)	(0.89)	(1.63)
sent transfers	-0.000	-0.000	0.000	0.000
	(-1.05)	(-0.97)	(1.33)	(1.70)
HSNP transfer	-0.255*	-0.245*	-0.104	0.0802
	(-3.48)	(-3.80)	(-1.04)	(0.83)
Wealth TLU				
Medium Class	0.116	0.681**	0.210*	0.501
	(0.93)	(5.43)	(3.77)	(2.53)
High Class	-1.607***	-0.722**	-0.942***	-1.667***
	(-10.29)	(-5.39)	(-7.64)	(-10.09)
Constant	9.373***	9.440***	8.047***	8.969***
	(24.62)	(18.30)	(37.22)	(55.47)
Specifications				
Drought Interactions	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes
N	3019	2427	2496	1847

robust standard error clustered at index area level in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Conclusion

The research aim of this paper was to investigate the conditions and outcomes of Index-Based Livestock Insurance (IBLI) uptake for the purpose of increasing smallholder livestock farmers' resilience to droughts in Kenya. To the best of our knowledge, this paper provides a unique comprehensive view on an index insurance project by considering different components of index insurance's capacity as a viable solution to extreme climate events for smallholder farmers.

Our first hypothesis explores the conditions of take up and particularly the role of livestock reducing drought events. We find insufficient evidence for livestock reducing drought events to be categorized as a relevant factor in the uptake of IBLI as speculated in the literature. While household head characteristics besides age do not exhibit relevance, mobile phone use and coupon use are strong mechanisms driving actual uptake IBLI.

Secondly, the outcomes of IBLI are considered through their impact on income and non-food consumption in the case of livestock loss due to drought. Our estimations do not provide a significant positive impact of the IBLI product on our two outcomes, suggesting that there is either no or even a weak negative direct impact in the case of livestock loss compared to non-insured households. These findings add to the literature by highlighting the limitations of index insurance and possibly explain their low demand.

Overall, our findings for the IBLI product point towards low demand, consistent with the literature, but also display a limited direct effect on insured households. The feasibility of this product as a large scale policy instrument is therefore questionable from both a cost and effectiveness standpoint. Considerable adjustments to product design and delivery tailored to the needs of smallholder farmers with consideration of local context would be necessary to make index insurance an effective climate risk management tool.

However, the apparent role of mobile phones access could provide an opportunity for success in product delivery and cost reduction. A recommendation would be the move towards mobile payout system for index insurance for an even faster and less costly insurance product. Growing technology, for example in remote sensing, could also provide new avenues for index insurance and considerably reduce basis risk.

This conclusion is context specific to IBLI product analyzed in this paper. Although the reviewed literature points to some coherence on the subject for other cases, this can only be confirmed through similar analysis on other cases with different contexts and types of index insurance. Future research could therefore focus on possible synergies between index insurance cases to provide a broader view on the subject.

Further notable limitations specific to the IBLI case concern the data. In terms of outcomes, usable data for food consumption is an important variable for vulnerable smallholder farmers missing from this investigation which should be considered for other cases. Additionally, the seasonal variation and biannual contract sales period could be exploited for differences in outcomes over seasons, as could be the different livestock types to provide further depth and specificity to results. Lastly, long-run implications could be addressed by exploiting the length of the IBLI program.

Overall, the findings highlight index-based livestock insurance (IBLI) product's limitations for increasing smallholder farmers' resistance to drought shocks. But they also present different opportunities, such as technological innovations, to overcome these.

8 References

Abugri, S. A., Amikuzuno, J. & Daadi, E. B. (2017). Looking out for a Better Mitigation Strategy: Smallholder Farmers' Willingness to Pay for Drought-Index Crop Insurance Premium in the Northern Region of Ghana, *Agriculture and Food Security*, [e-journal] vol. 6, no. 1, pp.1–9, Available Online: https://doi.org/10.1186/s40066-017-0152-2.

Adow, M. (2008). Pastoralists in Kenya, *Forced Migration Review*, [e-journal] no. 31, p.34, Available Online: http://search.proquest.com/docview/61708780?accountid=9851%5Cnhttp://tf5lu9ym5n.search.serialssolutions.com/?ctx_ver=Z39.88-2004&ctx_enc=info:ofi/enc:UTF-8&rfr_id=info:sid/ProQ:socabsshell&rft_val_fmt=info:ofi/fmt:kev:mtx:journal&rft.genre=article&rft.jtit.

Alderman, H. & Haque, T. (2007). Insurance Against Covariate Shocks, *World Bank*.

ARC. (2018). How ARC Works – African Risk Capacity, Available Online: http://www.africanriskcapacity.org/2016/10/29/how-arc-works/ [Accessed 19 April 2018].

Bageant, E. R. & Barrett, C. B. (2017). Are There Gender Differences in Demand for Index-Based Livestock Insurance?, *Journal of Development Studies*, [e-journal] vol. 53, no. 6, pp.932–952, Available Online: http://www.tandfonline.com/action/journalInformation?journalCode=fjds20 [Accessed 16 April 2018].

Barnett, B. J., Barrett, C. B. & Skees, J. R. (2008). Poverty Traps and Index-Based Risk Transfer Products, *World Development*, [e-journal] vol. 36, no. 10, pp.1766–1785, Available Online: https://www.sciencedirect.com/science/article/pii/S0305750X08001356 [Accessed 14 April 2018].

Barrett, C. B. (2011). Covariate Catastrophic Risk Management in the Developing World: Discussion, *American Journal of Agricultural Economics*, [e-journal] vol. 93, no. 2, pp.512–513.

Binswanger-Mkhize, H. (2012). Is There Too Much Hype about Index-Based Weather Index Insurance?, *Journal of Development Studies*, vol. 48, no. 2, pp.187–200.

Carter, M. R. & Barrett, C. B. (2006). The Economics of Poverty Traps and Persistent Poverty: An Asset-Based Approach, *Journal of Development Studies*, [e-journal] vol. 42, no. 2, pp.178–199, Available Online: http://www.tandfonline.com/doi/abs/10.1080/00220380500405261 [Accessed 29 May 2018].

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data, 325, *The Review of Economic Studies*, [e-journal] vol. 47, no. 1, p.225, Available Online: http://www.nber.org/papers/w0325.pdf [Accessed 17 May 2018].

Chambers, R., Pacey, A. & Thrupp, L. A. (1989). Farmer First : Farmer Innovation and Agricultural Research, [e-book] Intermediate Technology Publications, Available Online: https://books.google.es/books?hl=en&lr=&id=eA5xEALndC4C&oi=fnd&pg=PA5&dq=+Farmer+First:+Farmer+Innovation+and+Agricultural+Research+&ots=SAm0rcAw3e&sig=gQtO736wIy4_F1HPFEJlWtb5BbY#v=onepage&q=Farmer First%3A Farmer Innovation and Agricultural Research&f=false [Accessed 25 March 2018].

Chantarat, S. & Mude, A. (2009). Willingness to Pay for Index Based Livestock Insurance: Results from a Field Experiment in Northern Kenya, *Ithaca, NY (USA):*, [e-journal] pp.0–39, Available Online: https://cgspace.cgiar.org/bitstream/handle/10568/784/chantarat_et_al__wilingnes?sequence=2 [Accessed 22 April 2018].

Chantarat, S., Mude, A. G. & Barrett, C. B. (2009). Designing Index Based Livestock Insurance for Managing Livestock Asset Risk in Northern Kenya, *The Journal of Risk and Insurance*, Vol. 80, Available Online: http://www.jstor.org/stable/23354973 [Accessed 16 April 2018].

Chantarat, S., Mude, A. G., Barrett, C. B., Carter, M. R., Ikegami, M. & McPeak, J. G. (2010). Insuring Against Drought Related Livestock Mortality: Piloting Index Based Livestock Insurance in Northern Kenya, *SSRN Electronic Journal*, [e-journal] no. May, pp.1–25, Available Online: https://cgspace.cgiar.org/bitstream/handle/10568/16493/AGRA-ILRI-13-IBLI.pdf?sequence=1 [Accessed 23 April 2018].

Chantarat, S., Mude, A. G., Barrett, C. B. & Carter, M. R. (2013). Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya, *Journal of Risk and Insurance*, [e-journal] vol. 80, no. 1, pp.205–237, Available Online: http://doi.wiley.com/10.1111/j.1539-6975.2012.01463.x [Accessed 14 April 2018].

Cole, S., Stein, D. & Tobacman, J. (2014). Dynamics of Demand for Index Insurance: Evidence from a Long-Run Field Experiment, *American Economic Review*, [e-journal] vol. 104, no. 5, pp.284–290, Available Online: http://pubs.aeaweb.org/doi/10.1257/aer.104.5.284.

Dercon, S., Hill, R. V., Clarke, D., Outes-Leon, I. & Seyoum Taffesse, A. (2014). Offering Rainfall Insurance to Informal Insurance Groups: Evidence from a Field Experiment in Ethiopia, *Journal of Development Economics*, [e-journal] vol. 106, pp.132–143, Available Online: http://dx.doi.org/10.1016/j.jdeveco.2013.09.006.

Farrin, Katie; Murray, A. G. (2014). The Effect of Index Insurance on Returns to Farm Inputs: Exploring Alternatives to Zambia's Fertilizer Subsidy Program, *Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014*, [e-journal], Available Online: http://ageconsearch.umn.edu/bitstream/170240/2/AAEA_Index_Submit A.pdf.

Greatrex, H., Hansen, J., Garvin, S., Diro, R., Blakeley, S., Le Guen, M., Rao, K. & Osgood, D. (2015). Scaling up Index Insurance for Smallholder Farmers: Recent Evidence and Insights, *CCAFS Report*, Vol. 14, Available Online: https://cgspace.cgiar.org/bitstream/handle/10568/53101/CCAFS_Report14.pdf?sequence=1&isAllowed=y [Accessed 27 May 2018].

Hess, U. & Hazell, P. (2013). Innovations and Emerging Trends in Agricultural Insurance, *Deutsche Gesellschaft Für Internationale Zusammenarbeit (GIZ)*, Bonn, Germany, Available Online: https://www.giz.de/fachexpertise/downloads/giz-2016-en-innovations_and_emerging_trends-agricultural_insurance.pdf [Accessed 29 May 2018].

Hochrainer-Stigler, S., van der Velde, M., Fritz, S. & Pflug, G. (2014). Remote Sensing Data for Managing Climate Risks: Index-Based Insurance and Growth Related Applications for Smallhold-Farmers in Ethiopia, *Climate Risk Management*, [e-journal] vol. 6, pp.27–38, Available Online: http://dx.doi.org/10.1016/j.crm.2014.09.002.

Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M. & Meinke, H. (2007). Adapting Agriculture to Climate Change., *Proceedings of the National Academy of Sciences of the United States of America*, [e-journal] vol. 104, no. 50, pp.19691–6, Available Online: http://www.ncbi.nlm.nih.gov/pubmed/18077402 [Accessed 23 March 2018].

IFC. (2018). Index Insurance - Frequently Asked Questions, Available Online: http://www.ifc.org/wps/wcm/connect/industry_ext_content/ifc_external_corporate_site/i

ndustries/financial+markets/retail+finance/insurance/index+insurance+-+frequently+asked+questions [Accessed 25 March 2018].
Ikegami, M. & Sheahan, M. (2017). Index Based Livestock Insurance (IBLI) Marsabit Household Survey Codebook.
Isaboke, H. N., Analysis, I., Division, E., Qiao, Z., Analysis, I., Division, E., Information, A., Nyarindo, W. N., Ke, W., Analysis, I., Division, E. & Information, A. (2016). Explaining the Perception of Smallholders towards Weather Index Micro-Insurance alongside Risk and Coping Strategies, *International Journal of Food and Agricultural Economics*, vol. 4, no. 4, pp.59–77.
Isakson, S. R. (2015). Derivatives for Development? Small-Farmer Vulnerability and the Financialization of Climate Risk Management, *Journal of Agrarian Change*, vol. 15, no. 4, pp.569–580.
Jack, W. & Suri, T. (2011). Mobile Money: The Economics of M-PESA, Available Online: http://www.nber.org/papers/w16721.pdf.
Jensen, N., Barrett, C. & Mude, A. (2015). The Favourable Impacts of Index-Based Livestock Insurance: Evaluation Results from Ethiopia and Kenya, *ILRI Research Brief—May*, [e-journal] no. May, Available Online: https://cgspace.cgiar.org/bitstream/handle/10568/66652/ResearchBrief52.pdf?sequence=1 [Accessed 23 April 2018].
Jensen, N., Mude, A., Barrett, C., Jensen, N. D., Mude, A. G. & Barrett, C. B. (2016). How Basis Risk and Spatiotemporal Adverse Selection Influence Demand for Index Insurance: Evidence from Northern Kenya, 72484, Available Online: https://mpra.ub.uni-muenchen.de/72484/ [Accessed 24 April 2018].
Jensen, N. D., Barrett, C. B. & Mude, A. G. (2016). Index Insurance Quality and Basis Risk: Evidence from Northern Kenya, *American Journal of Agricultural Economics*, [e-journal] vol. 98, no. 5, pp.1450–1469, Available Online: https://academic.oup.com/ajae/article-abstract/98/5/1450/2415540?redirectedFrom=fulltext [Accessed 19 April 2018].
John, F., Toth, R., Frank, K. & Müller, B. (2017). Ecological Vulnerability through Insurance? Potential Unintended Consequences of Index-Based Livestock Insurance, [e-journal], Available Online: http://www.bioecon-network.org/pages/19th_2017/Felix.pdf [Accessed 18 April 2018].
Johnson, L. (2013). Index Insurance and the Articulation of Risk-Bearing Subjects, *Environment and Planning A*, [e-journal] vol. 45, pp.2663–2681, Available Online: http://journals.sagepub.com/doi/pdf/10.1068/a45695?id=a45695& [Accessed 30 May 2018].
Leblois, A., Quirion, P., Alhassane, A. & Traoré, S. (2014). Weather Index Drought Insurance: An Ex Ante Evaluation for Millet Growers in Niger, *Environmental and Resource Economics*, vol. 57, no. 4, pp.527–551.
Makaudze, E. M. & Miranda, M. J. (2010). Catastrophic Drought Insurance Based on the Remotely Sensed Normalised Difference Vegetation Index for Smallholder Farmers in Zimbabwe, *Agrekon*, vol. 49, no. 4, pp.418–432.
Marenya, P., Smith, V. H. & Nkonya, E. (2014). Relative Preferences for Soil Conservation Incentives among Smallholder Farmers: Evidence from Malawi, *American Journal of Agricultural Economics*, vol. 96, no. 3, pp.690–710.
Mileti, D. (1999). Disasters by Design : A Reassessment of Natural Hazards in the United States., [e-book] National Academies Press, Available Online: https://books.google.es/books?hl=en&lr=&id=Atw7c6vshAYC&oi=fnd&pg=PT21&dq=mileti+1999&ots=ag4p74gGLD&sig=t_oo_bC5JFfS6p_tTCQ7XD1xu20#v=onepage&q=mileti 1999&f=false [Accessed 30 May 2018].

Morton, J. F. (2007). The Impact of Climate Change on Smallholder and Subsistence Agriculture., *Proceedings of the National Academy of Sciences of the United States of America*, [e-journal] vol. 104, no. 50, pp.19680–5, Available Online: http://www.ncbi.nlm.nih.gov/pubmed/18077400 [Accessed 23 March 2018].

Mude, A., Barrett, C. B., Carter, M. R., Chantarat, S., Ikegami, M. & McPeak, J. G. (2009). Index Based Livestock Insurance for Northern Kenya's Arid and Semi-Arid Lands: The Marsabit Pilot, *SSRN Electronic Journal*, [e-journal] no. January, Available Online: http://barrett.dyson.cornell.edu/files/papers/IBLI_PROJECT_SUMMARY.pdf [Accessed 23 April 2018].

Mude, A. (2014). East African Herders Insure against Drought: An Impact Narrative from Kenya and Ethiopia, *ILRI Research Brief 23*, Available Online: https://cgspace.cgiar.org/bitstream/handle/10568/43765/Research_brief_23.pdf?sequence=4 [Accessed 23 April 2018].

Müller, B., Johnson, L. & Kreuer, D. (2017). Maladaptive Outcomes of Climate Insurance in Agriculture, *Global Environmental Change*, [e-journal] vol. 46, no. November 2016, pp.23–33, Available Online: http://dx.doi.org/10.1016/j.gloenvcha.2017.06.010.

O'Brien, K. L. & Leichenko, R. M. (2000). Double Exposure: Assessing the Impacts of Climate Change within the Context of Economic Globalization, *Global Environmental Change*, [e-journal] vol. 10, no. 3, pp.221–232, Available Online: https://www.sciencedirect.com/science/article/pii/S0959378000000212 [Accessed 30 May 2018].

Patt, A., Suarez, P. & Hess, U. (2010). How Do Small-Holder Farmers Understand Insurance, and How Much Do They Want It? Evidence from Africa, *Global Environmental Change*, vol. 20, no. 1, pp.153–161.

Peterson, N. D. (2012). Developing Climate Adaptation: The Intersection of Climate Research and Development Programmes in Index Insurance, *Development and Change*, vol. 43, no. 2, pp.557–584.

Pforr, K. (2013). How to Interpret the Logistic Regression with Fixed Effects, Available Online: https://www.europeansurveyresearch.org/conf/uploads/174/103/128/pforr_ESRA2013_interpretation_fixed_effects_logit.pdf [Accessed 17 May 2018].

Ricome, A., Affholder, F., Gérard, F., Muller, B., Poeydebat, C., Quirion, P. & Sall, M. (2017). Are Subsidies to Weather-Index Insurance the Best Use of Public Funds? A Bio-Economic Farm Model Applied to the Senegalese Groundnut Basin, *Agricultural Systems*, vol. 156, no. October 2016, pp.149–176.

Schulz, K. F. & Grimes, D. A. (2002). Sample Size Slippages in Randomised Trials: Exclusions and the Lost and Wayward, *The Lancet*, [e-journal] vol. 359, no. 9308, pp.781–785, Available Online: http://www.ncbi.nlm.nih.gov/pubmed/11888606 [Accessed 20 May 2018].

Smith, V. H. (2016). Producer Insurance and Risk Management Options for Smallholder Farmers, *World Bank Research Observer*, vol. 31, no. 2, pp.271–289.

Smith, V. H. & Glauber, J. W. (2012). Agricultural Insurance in Developed Countries: Where Have We Been and Where Are We Going?, *Applied Economic Perspectives and Policy*, [e-journal] vol. 34, no. 3, pp.363–390.

Tadesse, M. A., Shiferaw, B. A. & Erenstein, O. (2015). Weather Index Insurance for Managing Drought Risk in Smallholder Agriculture: Lessons and Policy Implications for Sub-Saharan Africa, *Agricultural and Food Economics*, [e-journal] vol. 3, no. 1, Available Online: http://dx.doi.org/10.1186/s40100-015-0044-3.

Takahashi, K., Ikegami, M., Sheahan, M. & Barrett, C. B. (2016). Experimental Evidence on the Drivers of Index-Based Livestock Insurance Demand in Southern Ethiopia, *World*

Development, [e-journal] vol. 78, pp.324–340, Available Online: https://www.sciencedirect.com/science/article/pii/S0305750X15002612 [Accessed 15 April 2018].

Turvey, C. G. & Mclaurin, M. K. (2012). Applicability of the Normalized Difference Vegetation Index (NDVI) in Index-Based Crop Insurance Design, *Weather, Climate, and Society*, [e-journal] vol. 4, no. 4, pp.271–284, Available Online: https://journals.ametsoc.org/doi/pdf/10.1175/WCAS-D-11-00059.1 [Accessed 1 April 2018].

UNFCCC. (2018). Risk Management Approaches to Address Adverse Effects of Climate Change - Insurance, Available Online: http://unfccc.int/cooperation_support/response_measures/items/4971.php#IBI [Accessed 26 February 2018].

UNFCCC. (2008). Mechanisms to Manage Financial Risks from Direct Impacts of Climate Change in Developing Countries, Available Online: http://unfccc.int/resource/docs/2008/tp/09.pdf.

Vrieling, A., Meroni, M., Shee, A., Mude, A. G., Woodard, J., de Bie, C. A. J. M. & Rembold, F. (2014). Historical Extension of Operational NDVI Products for Livestock Insurance in Kenya, *International Journal of Applied Earth Observation and Geoinformation*, [e-journal] vol. 28, no. 1, pp.238–251, Available Online: http://dx.doi.org/10.1016/j.jag.2013.12.010.

Weier, J. & Herring, D. (2000). Measuring Vegetation (NDVI & EVI), *Feature Articles*, Available Online: https://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_1.php [Accessed 11 April 2018].

Wang, H. H., Karuaihe, R. N., Young, D. L. & Zhang, Y. (2013). Farmers' Demand for Weather-Based Crop Insurance Contracts: The Case of Maize in South Africa, *Agrekon*, [e-journal] vol. 52, no. 1, pp.87–110, Available Online: http://www.tandfonline.com/doi/abs/10.1080/03031853.2013.778468.

Williams, R. (2017). Panel Data 3: Conditional Logit/ Fixed Effects Logit Models, Available Online: http://www3.nd.edu/~rwilliam/ [Accessed 17 May 2018].

Yang, Y. (2010). Weather Index Derivatives in Risk Transfer for Agricultural Natural Hazards, *Agriculture and Agricultural Science Procedia*, [e-journal] vol. 1, pp.100–105, Available Online: http://dx.doi.org/10.1016/j.aaspro.2010.09.012.

9 Appendix

Appendix Table 1. Dates of household survey rounds, sales, and indemnity pay-out periods

Date	Activity
October-November 2009	Household survey round 1
January-February 2010	1st IBLI sales period
October-November 2010	Household survey round 2
January-February 2011	2nd IBLI sales period
August-September 2011	3rd IBLI sales period
October-November 2011	Household survey round 3
October-November 2011	1st IBLI indemnity payout
March-April 2012	2nd IBLI indemnity payout
August-September 2012	4th IBLI sales period
October-November 2012	Household survey round 4
January-February 2013	5th IBLI sales period
August-September 2013	6th IBLI sales period
March-April 2013	3rd IBLI indemnity payout
October-November 2013	Household survey round 5
January-February 2014	7th IBLI sales period
March-April 2014	4th IBLI indemnity payout
August-September 2014	8th IBLI sales period
October-November 2014	5th IBLI indemnity payout
January-February 2015	9th IBLI sales period
March-April 2015	6th IBLI indemnity payout
August 2015	7th IBLI indemnity payout
August-September 2015	10th IBLI sales period
October-November 2015	Household survey round 6

Source: IBLI Marsabit Household Survey Codebook (Ikegami & Sheahan, 2017)

Appendix Table 2. Overview Variables

Name	Type	Definition & Measurement
		Household Head Characteristics
age	continuous	Age of household head
sex	binary	Gender of household head (male=1)
noeducation	categorical	Education attendance of household head (no attendance=0)
marital status	binary	Marital status of household head(married=1)
ethnicity	categorical	Ethnic group of household head
religion	categorical	Religion household head
		Household Characteristics
household size	continuous	Household Size
mean age	continuous	Mean age of household members
mean education	continuous	Mean years of education of household members
income	continuous	Income of household in past year (KSh)
food expenditures	continuous	Food expenditure of household in past 7 days (KSh)
other expenditures	continuous	Other non-food consumption expenditures of household (KSh)
sent transfers	continuous	Household sent cash or in-kind transfers over last year (KSh)
received transfers	continuous	Household received cash or in-kind transfers over last year (KSh)
HSNP transfer	binary	Household received Hunger Safety Net Program (HSNP) transfer (yes=1)
other aid	binary	Household received any other aid transfer[20] (yes=1)
land ownership	binary	Household ownership of irrigated or non-irrigated land (yes=1)
low TLU class	binary	Lowest wealth classification (under 10 TLU)[21]
medium TLU class	binary	Medium wealth classification (between 10 and 20 TLU)
high TLU class	binary	Highest wealth classification (over 20 TLU)
		Livestock Characteristics
livestock expenses	continuous	Household livestock expenses (KSh)[22]
owned animals	continuous	Owned Tropical Livestock Units (TLU)[23]
herded animals	continuous	Herded Tropical Livestock Units (TLU)
animals Lost	continuous	TLU lost by household
adult TLU loss	continuous	Adult TLU lost by household
drought TLU loss	continuous	TLU lost to drought/starvation
other TLU loss	continuous	TLU lost to other causes[24]
		Financial Access & Insurance (IBLI)
bank account	binary	Household has money in bank account (yes=1)
lent	binary	Household has lent out money (yes=1)
merry-go-round	binary	Participation in merry-go-round (participation=1)
celluse daily	binary	Cell-use at least once per day (yes=1)
insured	binary	Insured through IBLI (yes=1)
insured animals	continuous	TLU insured through IBLI
insurance cost	continuous	Insurance cost of IBLI
coupon	binary	Received discount coupon for IBLI (yes=1)
game	binary	Played Educational game with IBLI (yes=1)
		Index Area Dummies (Division)
Central	binary	Household located in Central division (yes=1)
Gadamoji	binary	Household located in Gadamoji division (yes=1)
Laisamis	binary	Household located in Laisamis division (yes=1)
Loiyangalani	binary	Household located in Loiyangalani division (yes=1)
Maikona	binary	Household located in Maikona division (yes=1)

Source: Author

[20] Other aid transfers include: food aid, school feeding, supplementary feeding programs, cash for work program participation, NGO aid, government aid, county aid, emergency aid.

[21] TLU class is a household wealth classification based on livestock holdings categorised the following way: (1) low, meaning less than 10 TLU; (2) medium, with between 10 and 20 TLU; and (3) high, owning more than 20 TLU.

[22] Livestock expenses include: water, fodder, supplementary feeding, veterinary, transportation cost, other expenses & wages

[23] 1 TLU = 1 cow = 0.7 camels = 10 goats or sheep

[24] other causes include: disease, predation, raiding/rustling/conflict, accident/poisoned, lost, rain, premature birth, old age

Appendix Table 3. Summary Statistics by Survey Round and Insurance Status (1/2)

	Round 2			**Round 3**			**Round 4**		
	Mean (Insured)	Mean (Non-Insured)	Diff.	Mean (Insured)	Mean (Non-Insured)	Diff.	Mean (Insured)	Mean (Non-Insured)	Diff.
age	39.84	44.61		45.43	48.62	**	50.4	48.55	
age squared	1661.14	2183.48		2277.04	2635.7	**	2730.32	2616.04	
sex	0.1	0.17	*	0.59	0.59		0.63	0.6	
marital status	0.88	0.81		0.85	0.83		0.92	0.82	
ethnicity burji	0.03	0.02		0.03	0.02	***	0.01	0.03	***
ethnicity borana	0.13	0.08	***	0.07	0.10	**	0.13	0.09	
ethn. rendille	0.24	0.37	***	0.42	0.31		0.43	0.33	**
ethn. samburu	0.17	0.11		0.19	0.11		0.06	0.14	**
ethn. turkana	0.11	0.18	***	0.14	0.17		0.06	0.18	*
ethnicity gabra	0.30	0.21		0.12	0.27	***	0.25	0.23	
religion	3.04	3.08		3.24	3.01		3.73	3	***
household size	2.17	2.28		6.25	5.71	***	6.37	6.13	
mean age	8.4	9.73		21.26	23.53	***	23.12	23.01	
mean education	1.82	1.33	***	1.44	1.47		1.55	1.47	
income	67660.45	52774.47		53117.56	51748.1		80199.55	70174.14	
food exp.	1637.48	1232.2	***	18311.67	65990.45		2366.57	9708.29	**
other exp.	25320.83	18052.34	***	43856.47	34251.59		44779.97	49317.9	
rec. transfers	5028.29	6150.12		4375.98	4882.73		5055.67	5476.24	
sent transfers	2889.45	2545.64		5227.27	2670.76		3537.25	2392.38	
HSNP transfer	0	0		0.31	0.37	*	0.34	0.31	
other aid	0.91	0.93		0.99	0.98		0.95	0.97	
land ownership	0.15	0.1	***	0.2	0.17		0.25	0.17	
L TLU class	0.57	0.61		0.56	0.61	*	0.53	0.61	
M TLU class	0.23	0.24		0.23	0.23		0.23	0.23	
H TLU class	0.2	0.16		0.2	0.15	*	0.24	0.16	*
livestock exp.	1009.11	1399.66		4739.68	3253.32		2300.31	2193.45	
owned animals	8.66	12	***	8.88	7.17	**	9.8	7.78	
herded animals	9.48	14.72	***	10.27	8.85		9.93	8.11	
TLU loss	3.08	2.85		6.57	6.58		3.29	3.08	*
adult TLU loss	2.43	2.1		3.89	4.43		2.52	2.27	*
droughtloss dummy	0.6	0.65		0.87	0.92		0.66	0.69	
drought loss	1.34	1.07		3.7	4.17		0.96	0.88	
other loss	1.63	1.64		2.88	2.28	*	2.71	2.39	**
bank account	0.05	0.05		0.07	0.04		0.03	0.08	
lent	0.17	0.12		0.09	0.07		0.07	0.1	
merry-go-round	0.11	0.04	***	0.07	0.06		0.07	0.04	
celluse daily	0.32	0.16	***	0.21	0.22		0.37	0.31	*
discount coupon	0.00	0.85	***	0.00	0.59	***	0.71	0.56	**
game	0.00	0.00		0.00	0.00		0.00	0.00	
Maikona	0.29	0.19		0.11	0.24	***	0.24	0.2	
Central	0.08	0.13	***	0.13	0.11		0.07	0.11	
Gadamoji	0.11	0.05	***	0.06	0.06		0.09	0.06	
Laisamis	0.25	0.2		0.33	0.16	***	0.33	0.19	*
Loiyangalani	0.22	0.38	***	0.33	0.32		0.24	0.32	

Source: Author

* p<0.05, ** p<0.01, *** p<0.001

Appendix Table 3. Summary Statistics by Survey Round and Insurance Status (2/2)

	Round 5			**Round 6**		
	Mean (Insured)	Mean (Non-Insured)	Diff.	Mean (Insured)	Mean (Non-Insured)	Diff.
age	48.72	49.49		52.48	51.14	
age squared	2559.92	2692.72		2886.63	2833.74	
sex	0.62	0.61		0.89	0.59	
marital status	0.82	0.84		1	0.83	
ethnicity burji	0.00	0.03	***	0.00	0.03	**
ethnicity borana	0.03	0.09		0.00	0.09	
ethn. rendille	0.59	0.33		0.42	0.33	*
ethn. samburu	0.01	0.13		0.00	0.14	
ethn. turkana	0.27	0.16		0.03	0.17	
ethnicity gabra	0.10	0.24		0.49	0.23	**
religion	3.23	3.04		2.94	3.05	
household size	6.34	6.2		6.78	6.52	
mean age	22.07	23.4		23.15	24.29	
mean education	1.5	1.48		1.52	1.49	
income	86647.39	78700.16	**	109407.06	86011.22	
food expenditure	8904.6	7311.48		10687.86	7822.74	**
other expenditure	52801.27	45753.63		3382.75	3399.28	
received transfers	9027.12	6510.66	**			
sent transfers	2916.57	3870.01				
HSNP transfer	0.17	0.26		0.73	0.42	**
other aid	0.79	0.88		0.9	0.92	
land ownership	0.2	0.13		0.07	0.14	
low TLU class	0.51	0.61		0.4	0.6	
medium TLU class	0.24	0.23		0.26	0.23	
high TLU class	0.25	0.16		0.33	0.16	
livestock expenses	3447.8	2342.72	***	5493.51	4206.52	
owned animals	9.21	8.43		10.5	7.92	*
herded animals	9.81	8.87		10.99	8.7	
TLU loss	1.32	1.71		2.85	2.74	
adult TLU loss	1.01	1.19		1.59	1.85	
droughtloss dummy	0.4	0.57	**	1.74	1.33	**
drought TLU loss	0.16	0.41	**	0.83	0.83	
other TLU loss	1.16	1.36		1.21	1.43	
bank account	0.08	0.09		0.06	0.05	
lent	0.09	0.11		0.15	0.18	
merry-go-round	0.04	0.04		0.12	0.06	
celluse daily	0.52	0.29	***	0.79	0.63	
discount coupon	0.00	0.93	***	0.00	0.00	
game	0.00	0.00		0.00	0.00	
Maikona	0.27	0.2		0.53	0.19	**
Central	0.13	0.11		0.01	0.11	
Gadamoji	0.17	0.05	**	0	0.06	
Laisamis	0.34	0.19	***	0.28	0.19	
Loiyangalani	0.05	0.32	***	0.14	0.3	

Source: Author

* p<0.05, ** p<0.01, *** p<0.001

Appendix Table 4. Summary Statistics by Replacement and Repeat Households

	Mean(Replacement)	Mean(Repeat)	Diff.
Household Head Characteristics			
age	50.43	49.24	-1.02
age squared	2826.08	2667.05	-107.24
sex	0.62	0.6	-0.03
marital status	0.75	0.84	0.10***
ethnicity burji	0.02	0.03	0.01
ethnicity borana	0.08	0.09	0.05
ethnicity rendille	0.25	0.34	-0.06
ethnicity samburu	0.11	0.13	-0.02
ethnicity turkana	0.29	0.16	-0.04
ethnicity gabra	0.24	0.23	0.05
religion	2.79	3.07	0.51***
Household Characteristics			
household size	5.78	6.2	0.69***
mean age	23.58	23.38	-1.38
mean education	1.71	1.47	-0.44**
income	47867.49	73004.92	14804.61
other expenditure	31452.3	44370.62	13201.5
received transfers	5629.43	6336.56	-1239.25
sent transfers	2463.34	3298.11	637.53
HSNP transfer	0.35	0.33	-0.07
other aid	0.9	0.94	0.01
land ownership	0.09	0.16	0.09**
low TLU class	0.69	0.6	-0.07
medium TLU class	0.19	0.24	0.12***
high TLU class	0.11	0.17	0.08*
Livestock Characteristics			
livestock expenses	2732.26	3132.33	194.56
owned animals	5.19	8.1	2.26**
herded animals	6.7	8.86	2.11
TLU loss	4.96	3.57	-0.92
adult TLU loss	3.32	2.42	-0.37
droughtloss dummy	0.91	0.74	-0.17***
drought TLU loss	2.95	1.7	-0.88*
other TLU loss	1.71	1.92	0.09
Financial Access & Insurance (IBLI)			
bank account	0.04	0.07	0.04
lent	0.1	0.11	-0.05*
merry-go-round	0.02	0.05	0.01
celluse daily	0.42	0.37	-0.07
discount coupon	0.00	0.59	0.60***
game	0.00	0.00	0.00
Index Area Dummies (Division)			
Maikona	0.04	0.21	0.22***
Central	0.02	0.11	0.08***
Gadamoji	0.01	0.06	0.10***
Laisamis	0	0.21	0.16***
Loiyangalani	0.04	0.32	0.21***

Notes: Sample weights as reported in the dataset were used to correct possible oversampling.
The reported currency is the Kenyan Shilling (KSh), with 75KSh = US$1 in 2009.
* p<0.05, ** p<0.01, *** p<0.001

Appendix Table 5. Exogeneity of Drought Livestock Loss Dummy

insured (IBLI)	-0.0273
	(-1.33)
age	-0.0000311
	(-0.06)
sex	-0.0436
	(-1.58)
marital status	0.0127
	-0.62
ethnicity	0.00305
	-0.45
household size	-0.00284
	(-0.82)
mean education	-0.00335
	(-0.55)
income	0.000
	-0.56
received transfers	-0.000000697
	(-1.42)
sent transfers	0.00000142
	-1.82
HSNP transfer	0.0106
	-0.9
bank account	-0.0279
	(-0.99)
merry-go-round	-0.0639
	(-1.66)
celluse daily	0.0279
	-1.96
herded animals	-0.000341
	(-0.86)
M TLU Class	0.00277
	(-0.13)
H TLU Class	0.0251
	(-1.52)
Constant	0.988***
	(-30.94)

t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001

Appendix Table 6. IBLI Adoption (excl. coupons dummy)

	(1)	(2)	(3)	(4)
age	0.996	0.995	0.995	0.995
	(-0.98)	(-1.60)	(-1.73)	(-1.63)
sex	0.831	0.831	0.891	0.898
	(-1.04)	(-1.37)	(-0.60)	(-0.54)
marital status	1.083	1.056	0.984	0.950
	(0.34)	(0.28)	(-0.05)	(-0.18)
household size	1.036	1.036	1.046	1.045
	(1.23)	(1.15)	(1.64)	(1.56)
mean education	0.954	0.960	0.951	0.958
	(-1.11)	(-0.79)	(-1.02)	(-0.83)
income	1.000	1.000	1.000	1.000
	(0.66)	(0.28)	(0.95)	(-0.02)
livestock expenses	1.000	1.000	1.000	1.000
	(1.11)	(1.31)	(1.11)	(1.15)
owned animals	1.009	1.011	1.010	1.011
	(1.57)	(1.09)	(1.05)	(1.12)
drought loss dummy	0.940	0.915	0.935	0.909
	(-0.39)	(-0.77)	(-0.63)	(-0.82)
drought TLU loss	0.998	0.999	0.998	0.998
	(-0.11)	(-0.08)	(-0.19)	(-0.14)
HSNP transfer	1.085	1.095	1.080	1.089
	(0.51)	(0.37)	(0.29)	(0.32)
bank account	0.781	0.787	0.720	0.722
	(-0.92)	(-0.61)	(-0.93)	(-0.89)
merry-go-round	1.147	1.125	1.039	1.010
	(0.51)	(0.30)	(0.10)	(0.03)
cell use daily	1.989***	1.995***	1.962***	1.964***
	(3.91)	(8.09)	(6.76)	(6.35)
Wealth TLU				
M TLU class	1.136	1.161	1.146	1.170
	(0.79)	(1.32)	(1.22)	(1.41)
H TLU class	1.442*	1.467	1.449	1.474
	(2.23)	(1.48)	(1.42)	(1.50)
Specifications				
Ethnicity Control	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes
Heckman Correction			Yes	Yes
F-Test IM Ratio Chi2			55.27***	286.30***
N	3592	2749	3592	2749

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Results are presented in odds ratios.

Appendix Table 7. IBLI Impact on LN Income

	(5)	(6)	(7)	(8)	(9)	(10)
droughtloss dummy	0.0279	-0.00193	0.00667	-0.0201	0.0816	0.0588
	(0.29)	(-0.04)	(0.06)	(-0.35)	(0.78)	(0.89)
insured (IBLI)	0.270	0.245				
	(0.96)	(0.88)				
insurance*droughtloss	-0.393	-0.423	-0.139	-0.208*	-0.207	-0.245***
	(-1.70)	(-1.52)	(-1.33)	(-3.13)	(-1.95)	(-7.52)
insured animals (IBLI)			0.00322	0.0106	0.00301	0.0127
			(2.14)	(1.95)	(1.65)	(1.57)
other TLU loss					0.0242	0.0263*
					(2.30)	(3.45)
age	0.00661	0.00821	0.00655	0.00798	0.00744	0.00898
	(1.98)	(0.89)	(2.00)	(0.89)	(1.93)	(1.00)
sex	-0.0534	-0.164	-0.0485	-0.158	-0.167	-0.236
	(-0.36)	(-0.60)	(-0.33)	(-0.61)	(-0.88)	(-0.90)
household size	0.0942**	0.0910	0.0931**	0.0907	0.0757	0.0628*
	(4.16)	(2.40)	(4.10)	(2.40)	(2.23)	(3.12)
livestock expenses	0.000	0.000	0.000	0.000	0.000	0.000
	(2.06)	(0.77)	(2.06)	(0.76)	(1.31)	(0.64)
owned animals	0.0124*	0.0180*	0.0126*	0.0183*	0.0142**	0.0187*
	(3.36)	(3.85)	(3.34)	(3.58)	(4.14)	(3.49)
discount coupon	-0.0814	-0.0766	-0.0754	-0.0765	-0.210	-0.191*
	(-2.15)	(-1.14)	(-1.99)	(-1.20)	(-2.50)	(-3.90)
received transfers	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.87)	(-0.72)	(-0.91)	(-0.79)	(-0.93)	(0.83)
sent transfers	0.000	0.000	0.000	0.000	0.000	0.000
	(1.09)	(1.02)	(1.09)	(1.02)	(1.52)	(1.83)
HSNP transfer	-0.198	-0.228*	-0.196	-0.225*	-0.213*	-0.197*
	(-2.21)	(-3.00)	(-2.12)	(-2.94)	(-2.84)	(-2.71)
bank account	0.197*	0.126	0.197*	0.127	0.170*	0.0633
	(2.62)	(1.62)	(2.67)	(1.64)	(2.86)	(0.53)
merry-go-round	0.0755	-0.0643	0.0588	-0.0736	0.143	-0.128
	(0.89)	(-1.03)	(0.88)	(-1.27)	(1.10)	(-1.47)
celluse daily	0.162	0.214	0.165	0.216	0.167	0.173
	(2.04)	(2.28)	(2.04)	(2.20)	(2.41)	(1.61)
Wealth TLU						
M	0.282	0.703**	0.291	0.712**	-0.301	1.009***
	(1.90)	(5.30)	(2.07)	(5.99)	(-1.95)	(9.82)
H	-1.431***	-0.648**	-1.407***	-0.569*	-0.259	1.502*
	(-9.54)	(-4.71)	(-9.60)	(-3.56)	(-0.42)	(3.23)
Constant	8.862***	9.181***	8.880***	9.195***	8.664***	8.743***
	(45.22)	(27.81)	(46.60)	(30.13)	(35.12)	(23.51)
Specifications						
Division Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes	Yes	Yes
N	3019	2427	3019	2427	2452	1896

robust standard error clustered at index area level in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table 8. IBLI Impact on LN Consumption

	(5)	(6)	(7)	(8)	(9)	(10)
droughtloss dummy	0.120	0.128	0.0854	0.101	0.0941	0.0903
	(1.71)	(1.70)	(1.56)	(1.17)	(1.45)	(1.27)
insured (IBLI)	0.332	0.266				
	(1.50)	(1.07)				
insurance*droughtloss	-0.237	-0.255	0.0827	-0.00496	0.0778	-0.0341
	(-1.27)	(-1.48)	(1.14)	(-0.03)	(0.75)	(-0.20)
insured animals (IBLI)			-0.000	0.002	0.000	0.007
			(-0.11)	(0.58)	(0.09)	(1.17)
other TLU loss					0.00455	0.0185
					(0.81)	(1.12)
age	-0.00513	-0.0128	-0.00525	-0.0133	-0.00798*	-0.0192**
	(-0.74)	(-1.60)	(-0.74)	(-1.64)	(-3.15)	(-5.46)
sex	0.396	0.278	0.406	0.294	0.484	0.440
	(1.84)	(1.24)	(1.92)	(1.32)	(2.21)	(2.54)
household size	0.105*	0.112*	0.102*	0.110*	0.0737	0.127
	(3.54)	(3.74)	(3.61)	(3.94)	(1.53)	(2.49)
	0.000	0.000	0.000	0.000	0.000	0.000*
	(2.11)	(2.42)	(2.05)	(2.46)	(1.98)	(3.75)
livestock expenses	0.000	0.000	0.000	0.000	0.000	0.000
	(2.13)	(1.91)	(2.17)	(1.96)	(1.72)	(2.35)
owned animals	0.000	0.013*	0.0004	0.0138*	-0.000	0.013
	(0.01)	(2.94)	(0.14)	(3.60)	(-0.15)	(2.40)
discount coupon	0.0822	0.0856	0.0879	0.0885	0.0466	0.0855
	(0.84)	(0.92)	(0.86)	(0.92)	(0.41)	(0.86)
received transfers	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	(3.65)	(2.71)	(3.48)	(2.74)	(0.60)	(0.59)
sent transfers	0.000	0.000	0.000	0.000	0.000	0.000
	(1.70)	(2.47)	(1.55)	(2.31)	(0.84)	(1.00)
HSNP transfer	-0.242*	-0.0176	-0.245*	-0.0195	-0.271***	0.0186
	(-3.15)	(-0.20)	(-3.56)	(-0.21)	(-7.59)	(0.17)
bank account	0.108	0.128	0.107	0.128	-0.000	-0.0544
	(1.04)	(1.15)	(1.02)	(1.14)	(-0.00)	(-0.48)
merry-go-round	0.379	0.416	0.349	0.398	0.197	0.279*
	(2.31)	(2.44)	(2.26)	(2.38)	(2.07)	(2.60)
cell use daily	0.0578	0.0672	0.0627	0.0722	0.0673	0.148
	(0.82)	(1.70)	(0.88)	(1.82)	(0.68)	(1.66)
Wealth TLU						
M	0.282	0.703**	0.291	0.712**	-0.301	1.009***
	(1.90)	(5.30)	(2.07)	(5.99)	(-1.95)	(9.82)
H	-1.431***	-0.648**	-1.407***	-0.569*	-0.259	1.502*
	(-9.54)	(-4.71)	(-9.60)	(-3.56)	(-0.42)	(3.23)
Constant	8.862***	9.181***	8.880***	9.195***	8.664***	8.743***
	(45.22)	(27.81)	(46.60)	(30.13)	(35.12)	(23.51)
Specifications						
Division Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Excl. round 1&2		Yes		Yes	Yes	Yes
N	3019	2427	3019	2427	2452	1896

robust standard error clustered at index area level in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$