# BASIS RISK, UPTAKE AND IMPACTS OF INDEX BASED LIVESTOCK INSURANCE IN NORTHERN KENYA

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BASIS RISK, UPTAKE AND IMPACTS OF INDEX BASED LIVESTOCK INSURANCE IN NORTHERN KENYA

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Index insurance is a promising tool for fighting poverty where households face climactic uncertainty and incomplete financial markets. Although index insurance products avoid many of the costs that prohibit supply of conventional loss-indemnifying insurance for small holders in developing countries, index products expose insured households to basis risk because they can only insure covariate losses and indices are inevitably imperfect. Until now, no empirical study has examined the magnitude of basis risk in the context of the developing world. Nor have direct estimates of basis risk been included in demand analyses. Furthermore, the impacts of index based insurance on household welfare have been unknown.

This dissertation looks closely at basis risk, demand, and impacts of index insurance. The Index Based Livestock Insurance (IBLI) product, available to pastoralists in northern Kenya since 2010, provides an ideal setting for such an analysis. The IBLI index was constructed using methods explicitly designed to minimize basis risk and implementation included an in-depth longitudinal household survey.

The first paper finds that basis risk is substantial due to the high degree of variability between households and inaccuracies in the index. Although the existence of design risk is expected, the great deal of idiosyncratic risk is surprising in a region where large covariate droughts are

known to be the major cause of livestock mortality.

The second paper finds that product-related factors are at least as important as demographic and financial related characteristics in determining demand for IBLI. Both idiosyncratic risk and households' observed design risk play a large role in determining demand. In addition, a simplified premium schedule generated significant spatiotemporal adverse selection.

The third paper finds that IBLI coverage reduces precautionary savings held in livestock and increases investments in productivity through mobility and livestock veterinary services. These adjustments to production strategies are associated with increases in income from milk and income per adult equivalent. When compared to the costs and impacts of the Hunger Safety Net Program, an ongoing cash transfer program in the same region, IBLI performs quite well and may become even more cost effective as the initial costs are spread across more clients.

## BIOGRAPHICAL SKETCH

Nathaniel Jensen received his Bachelor of Arts in Physics and a minor in Mathematics from Luther College in Decorah, Iowa, in 2003. He then spent two years in Mali as a Peace Corps volunteer in the agricultural sector. Upon returning to the United States, he joined the Peace Corps Fellows program at the University of Missouri, Columbia, where he acted as a student leader in community development programs while studying in the Department of Agricultural and Applied Economics. He earned his M.S. from that department in 2010 with a thesis on livelihood strategies practiced by agro-pastoralists on the Bolivian *Altiplano*. He entered the Ph.D. program in Applied Economics and Management at Cornell University in August 2010.

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# Chapter 1: Introduction

## Introduction

An estimated 200 million pastoralists exist in the world today (Nori, Switzer & Crawford 2005). Characterized by a dependence on extensive livestock grazing for a large percentage of the household economic portfolio, pastoralism has evolved as a livelihood strategy in many arid and semi-arid lands where cropping is precarious and a scarcity of natural resources have held populations low (FAO 2001; Niamir-Fuller 1999). Pastoralists rely on their livestock to capture and concentrate the low-density biomass of the rangelands into nutrient rich food, providing the household with income, manure, traction power, financial instruments, and social status (Randolph et al. 2007).

In years with good precipitation, these arid and semi-arid regions provide extensive pastures and sufficient water sources to maintain large herds of cattle. During drought, however, forage dies and water becomes scarce, leaving livestock with little or no access to these essential resources. Disease outbreaks and increased wildlife predation due to scarcity of wild prey, exacerbate the water and forage stress during drought. The result is a boom and bust cycle in herd size that has been observed in many pastoral economies. Because pastoralist households are highly invested in livestock, a large portion of their wealth is thus susceptible to disease and climate shocks. When shocks such as droughts cause high livestock mortality, households lose a great deal of their productive capital as well as their in-kind savings, reducing both current and future income.

Households respond to the risk of such shocks by adjusting their consumption, savings, and production decisions to reduce their level of risk exposure and to protect their assets *ex ante.*

Once shocks occur, households can respond by selling assets, increasing labor, or reducing consumption. Unfortunately, in areas with few resources, these *ex post* strategies—such as distress sales of livestock, pulling children from school so that they can work, and reducing food intake—are often associated with serious long-term consequences for household welfare.

Pastoralist households in northern Kenya and southern Ethiopia rely on livestock to provide an estimated 64 percent of their income (McPeak et al. 2011).Similar to other pastoralists, their wealth is closely tied to livestock holdings, which are periodically decimated by drought. For example, during a drought in 2009, pastoralists in some areas of Kenya reported cattle mortality rates above 50% (Zwaagstra 2010). Again in 2011, a severe drought caused livestock mortality of 15-30% across the Horn of Africa, with pockets of mortality above 60% (USAID 2011, OCHA 2011).

The threat of climatic—and thus economic—shocks is only increasing in the region. Scientific analysis points towards reduced precipitation levels, increased precipitation variation, and increased occurrence of extreme weather events across southern Ethiopia and northern Kenya (Cooper 2008; Funk et al. 2010; Funk et al. 2012). At the same time, population growth is increasing land pressure as well as the number of people that are affected by each drought (Herrero et al. 2010).

An index-based livestock insurance (IBLI) product, designed by researchers from Cornell University, the International Livestock Research Institute (ILRI) and the University of California-Davis, was introduced in Marsabit region of northern Kenya in January 2010 and expanded into the Borana region of southern Ethiopia in mid-2012 (Chantarat et al. 2012). ILRI leads the implementation process, supporting local private insurance firms that sell the IBLI product directly to pastoralists. Theoretically, insurance can help households smooth their income over shocks and accelerate herd recovery following shocks, potentially mitigating some of the consequences of income uncertainty and sudden loss of assets and income. However, no empirical literature exists on the uptake or impacts of livestock insurance in the developing country context.

The objective of this research is to gain a better understanding of the role that insurance can play in helping pastoralist households increase their welfare and manage the risks they face due to drought and livestock mortality. The IBLI pilot in Marsabit, Kenya, provides an excellent opportunity to study the uptake and impact of an innovative insurance product within a population that historically had no access to formal insurance but has the potential to benefit tremendously from reduced asset and income uncertainty.

This dissertation is organized as four sections. This literature review chapter is followed by three original empirical papers, each addressing one important topic related to the potential strengths and shortcomings of index insurance products. Chapter 2 focuses on basis risk, or the risk that remains in the portfolio of IBLI insured households. We examine the impact that IBLI coverage has on the risk faced by households and then look more closely at contract and household level determinants of basis risk. This is the first such examination of basis risk for an index product in the developing world.

The second paper, Chapter 3, examines who purchases insurance and why. Drawing on studies of crop insurance, we examine the household and environmental factors associated with the decision to purchase IBLI. A unique feature of this study is the inclusion of idiosyncratic and design elements of basis risk, an often referenced but rarely measured potential barrier to insurance demand. This research is the first to empirically examine the impacts of basis risk on demand for an index insurance product in the developing world using direct estimates rather than proxy variables.

The third and final paper, Chapter 4, studies the impact that IBLI coverage has on household production strategies and welfare. We compare those impacts to that of an unconditional cash transfer (UCT) social safety net program in the same area. To the authors' knowledge, no study is as well suited to compare the impacts of a privately provided but publically supported insurance product with those of a publically provided UCT intervention. Comparing two interventions that take place simultaneously in the same location provides unique insight into the relative value of each of these publically funded interventions in an environment where other policy interventions are possible.

This research examines the quality of an index insurance product for livestock, who demands that insurance conditional on quality, and the impact that having coverage has on the household's production strategies and welfare. Not only is it the first impact assessment of a large scale livestock insurance product for pastoralists, it adds to the literature on basis risk, demand for index insurance, and the absolute and relative impacts of index insurance on pastoralist livelihoods.

## Background

### *Pastoralism*

Arid and Semi-Arid Lands (ASAL) are defined as those areas where annual precipitation falls between 0-300 mm and 300-600 mm respectively (FAO 1987). According to Brown (1963), areas receiving annual precipitation of 650-900mm are precarious for crops and areas receiving below 500 mm of annual precipitation are unsuitable for cropping, suitable only for rangelands. Rangelands are "uncultivated land[s] that can support grazing and browsing animals" (Herlocker 1999, 2).

Pastoral societies are those societies that have organized around the care and use of extensively grazing livestock. These herders use livestock to capture and concentrate the low-density biomass of rangelands into nutrient rich food (Randolph et al. 2007). Their extensive (rather than intensive) land-use strategies are designed to exploit the variable and scarce assets of their regions and are often the most efficient use of resources in these regions (Council for Agriculture Science and Technology 1999; Scoones 1994). Even where other investment opportunities exist, livestock can have the highest return. For example, in northern Kenya livestock investments have a higher rate of return than depositing cash in a bank account, even when averaging over drought years. Although one might argue that banks offer lower risk, pastoralists of the region expressed concern over the ethical behavior of bankers and the safety of their money in banks (McPeak 2005).

Because livestock play an important role in many aspects of pastoralists' livelihoods, climate shocks (such as droughts) that cause high livestock mortality have consequences across many dimensions of their lives. A study of households from northern Kenya and southern Ethiopia, for example, found that quarterly average income per person and herd size had a correlation coefficient of 0.64 during a drought in 2000 and subsequent recovery through 2002. In Dirib Gumbo, a community in northern Kenya, the 2000 drought combined with interethnic tension that restricted herd mobility resulted in livestock mortality that accounted for more than 80% of animal wealth (McPeak et al. 2011).

After such shocks occur, households can react with coping mechanisms such as reducing food intake, removing children from school, or distress selling of livestock. Such ex post strategies have detrimental impacts on both human capital formation and future productive capacity. Because *ex post* coping strategies are limited, households respond to their uncertain environment by reducing exposure to foreseeable shocks. Livestock accumulation, herd composition, and herd mobility are three important *ex ante* coping strategies for pastoralists in northern Kenya. Large herds are not only an expression of wealth; greater herd size is associated with both higher per capita income and lower income variation (McPeak et al. 2011). Greater pre-drought herd size has also been linked to increased post-drought herd size (Lybbert et al. 2004; McPeak 2005), indicating that holding a large herd is an effective strategy for increasing post-drought wealth and income.

Herd composition is another dimension that pastoralists use to adapt to their environment and meet their needs. Maintaining a diverse herd exploits the highly variable resources of arid and semi-arid rangelands. Mixing grazers and browsers, for example, allows herds to take advantage of grasses and leaves (Oba and Lusigi 1987), the availability of which changes with the seasons (Woodard 1988). Drought and disease resistance also vary by livestock species, as do regeneration rates. For example, goat herds are highly susceptible to drought, but regenerate quickly once vegetation has returned. Camels are more likely to survive drought, but take longer to begin reproducing after drought (McCabe 1987). Milking schedules also differ between species. Some species recover lactation status more quickly after droughts while others produce milk in greater quantities during average years (Herlocker 1999). Finally, herd diversity also allows households to utilize different members of their labor pool due to the variation in labor requirements among species.

Although climate shocks often impact entire communities, prior research has found high variation in livestock mortality rates experienced by households in the same community (Lybbert et al. 2004; McPeak & Barrett 2001) - highlighting that household characteristics and herding strategies such as herd migration and splitting are important factors in determining livestock mortality rates. Livestock mobility allows herders to transport resources (in the form of animal protein) to where they are needed or out of the way of danger, while providing income generation, manure, traction power, financial instruments, and social status (Randolph et al, 2007). Herd mobility increases herd productivity and drought survival rates on semi-arid rangelands (Little el al. 2008; Niamir-Fuller 1999; Scoones 1994).

Many of the pastoralists of northern Kenya and southern Ethiopia maintain a sedentary base camp and a mobile satellite camp. Herd splitting between base camp and seasonal pastures (and often among several seasonal pastures), reduces the risk exposure associated with any one location and increases herd mobility (Niamir-Fuller and Turner 1999). Base camps accommodate the young, elderly, and infirm (animals and humans) and allow some members to perform sedentary activities such as cropping or small business, thereby diversifying the household's income portfolio. Portfolio diversity can reduce exposure to risk and increase the household's flexibility, allowing it to redistribute resources among activities in response to shocks and changes in the environment (McCarthy & di Gregorio 2007). Diversification into non-livestock related activities seems to be a successful strategy in this region. Those households that diversify their income activities to include both livestock income and cash earnings have the greatest per capita income and expenditures (McPeak et al. 2011).

The satellite herds rely on their increased mobility to locate and capture resources, often moving between water points and pastures as the seasons progress. Mobility provides access to low cost fodder while contributing to pasture sustainability by allowing degraded pastures to rest (Niamir-Fuller 2005). Where pastures are open access or held as common property, satellite herds are free to practice opportunistic grazing, which increases average herd productivity and reduces production variability due to climate shocks (Niamir-Fuller 1999; Scoones 1994) and increases drought survival rates (Little el al. 2008).

***Insurance***

Households may respond to risk by practicing strategies that reduce uncertainty (e.g., precautionary savings, reducing uptake of new technologies, production strategies that reduce exposure to risk) even at the cost of reduced expected income (Ellis 1993; Fafchamps 1999). For pastoralists, the protection of livestock is especially important because the dynamics between herd size and mobility create low wealth equilibria that are difficult to escape (Barrett et al. 2006; Little et al. 2008; Lybbert et al. 2004). Herders actively work to maintain herd sizes sufficient to sustain mobility, avoiding livestock sales, even at the expense of income variability (Barrett et al. 2006; Carter &Lybbert 2012; Fafchamps, Udry & Czukas 1998; McPeak 2004).

Insurance is a risk management tool that relies on pooling risk across populations and over time to protect individuals against uncertain shocks. For risk-averse households, insurance provides a valuable service of reducing future asset or income uncertainty. With insurance coverage, households are able to make their production decisions with less uncertainty and allocate fewer resources to risk reduction.

Informal forms of insurance—such as social lending and livestock transfers—exist in many pastoral societies, but recent studies have brought into question the extent to which these social mechanisms are actually able to protect vulnerable households from shocks. Desta (1999) finds that livestock transfers least often go to the poorest households among the Boran pastoralists of southern Ethiopia. When a Boran household does experience catastrophic losses, there is evidence of redistribution, but the transfers are small, on the scale of 1 animal for every 30 lost (Lybbert et al. 2004). Gabra herders in northern Kenya express similar patterns where the "existing informal institution is not likely to provide major support to households attempting to escape poverty or confront the risk of asset loss" (McPeak 2006, p435).These findings are supported by Santos and Barrett (2011), who find that social lending among the Boran does not focus on the poorest. Rather it often excludes the poorest in favor of those in danger of falling into a lower wealth equilibrium. Huysentruyt et al. (2007) find that pastoralists may also use transfers as coordinating mechanisms to ensure pastoral safety against cattle raids. Here, transfers are made by the more livestock-wealthy to the less wealthy in order to induce migration by lifting the herd-size over the migration threshold.

Even in cases where social insurance mechanisms are alive and well, they are most effective at reducing risks due to idiosyncratic events so that an unaffected household can redistribute income to an affected household. Covariate shocks, such as droughts or floods, which impact the entire pool of participants are problematic for smaller risk pools such as those often found with informal insurance. For example, while the Boran maintain that they have a strong tradition of social insurance with a wide variety of mechanisms for redistributing livestock or access to livestock to households that have suffered a severe shock, they report that these systems are becoming strained under repeated severe droughts because all the households have suffered severe losses (Hurst et al. 2011). In any case, it seems unlikely that informal insurance mechanisms provide a substantial insurance service to pastoralists of the region today.

If informal insurance within the community is unable to fully protect households from the impact of shocks, there is potentially a critical role for formal insurance to improve the situation of households. Yet, provision of insurance in developing countries has met many barriers. Households with little wealth need contracts for small coverage. For insurance providers, many small contracts mean high per-contract transaction costs relative to the premium. Conventional insurance pays indemnities contingent on individual experiences or losses, which then need to be individually validated, increasing costs further. If the provider has poor information or individuals face heterogeneous risks, premiums need to be adjusted to fit the risks that individuals face. If not, the provider will face adverse selection as those with lower risk will be unwilling to pay premiums calculated to fit the mean risk faced by those offered that premium. Although adverse selection is not restricted to policies offered in developing countries, gathering information on the many potential policy purchasers adds to already high transactions costs. Moral hazard is an additional risk that providers may face. If insured households change their actions as a result of being insured in such a way that increases their likelihood of receiving indemnity payments, the original premium calculations will underestimate the risk that the now-insured household faces.

Even when providers are able to overcome the costs of providing insurance, demand is not guaranteed. Historically, insurance schemes in both the developed (e.g. Grace et al. 2003) and developing (e.g. Karlan et al. 2012; Mobarak & Rosenzweig 2012) world have struggled with low demand even when premiums are subsidized, generally contradicting the predictions of the standard neoclassical model.[1] In the developing country context, a number of factors beyond

[1] According to the standard neoclassical model, risk averse households will maximize utility by fully insuring when prices are actuarially fair, by underinsuring when prices include loadings, and will always demand less insurance as wealth increases if premiums include loadings (Mossin 1968).

price have been identified as affecting insurance demand including: lack of information (Pratt, Suarez & Hess 2010), social learning (Cai, de Janvry & Sadoulet 2011), mis-estimation of own risk (Johnson et al. 1993; Gao et al. 2011), asset thresholds (Chantarat et al. 2010), liquidity constraints (Binswanger-Mkhize 2012; Cole et al. 2012; Liu & Myers 2012) and basis risk (Binswanger-Mkhize 2012; Clarke 2011; Mobarak & Rosenzweig 2012). There is also mounting evidence that poverty traps may distort demand for insurance. Chantarat et al. (2009) find that price elasticity of demand changes dramatically across poverty thresholds for pastoralists in northern Kenya, and that households below asset thresholds may choose not to purchase insurance at all.

When insurance is available and households do purchase it, coverage should reduce the impact that the risk of realized covered shocks have on households. Pastoralists in Marsabit who have purchased IBLI report different anticipated coping strategies than their peers during a drought in 2011 (Janzen & Carter 2012). Nevertheless, there is little empirical evidence that supports the belief that increased access to insurance will benefit those in developing countries. This is especially evident in a number of articles written specifically about the potential of weather insurance, which include descriptions of existing programs but are unable to include a summary of observed impacts (e.g., Alderman & Haque 2007; Miranda & Farrin 2012). There are a number of potential explanations for this. First, although there have been many resources devoted to developing and providing insurance, there has been much less emphasis on quantifying its benefits (deNicola 2012). Second, many of the products that are available are still young and have not had time to have an impact. Catastrophic insurance, for example, may be available for years before conditions trigger a payout. Finally, the empirical studies that have been completed do not find consistent impacts.

*Index-Based Livestock Insurance (IBLI)*

Index insurance is one method for circumventing some of the many barriers to offering insurance to small farmers and pastoralists in low income countries. Index insurance is able to reduce costs associated with the validation of individual-specific claims and adverse selection by using an easily observed signal to insure covariate risk (Miranda & Farrin 2012).[2] Furthermore, because the index is largely unaffected by individual activities, moral hazard is largely avoided. Basis risk, or the difference between the index and the individual experiences of those that are insured, is a potential drawback of all index-based insurance products.

A commercially provided index-based livestock insurance (IBLI) product began being sold in the Marsabit region of northern Kenya in January of 2010. The IBLI contract is based on a sophisticated response function that predicts seasonal livestock mortality rate using observations of the normalized difference vegetation index (NDVI), a remotely collected indicator of relative rangeland quality (Chantarat et al. 2013). The rationale for the index is that mortality associated with droughts is a response to an accumulation of poor rangeland conditions over an extended period of time. The response function was estimated using regression analysis of historic NDVI and livestock mortality data.

IBLI offers insurance contracts for goats, sheep, cattle, and camels with premiums that reflect average market values in the region. A contract provides 12 months of coverage. Households have the option of purchasing insurance during two sales windows: the first in January and February before the start of the long rains, and the second in August and September before the

[2] Within a single index region over single time period, adverse selection should not pose an issue for index insurance. Among index regions and over time, inter-temporal and spatial adverse selection may remain.

start of the short rains. Each rainy season is followed by a dry season. If the index falls above its contractually specified strike level at the end of either dry season, the contract will make indemnity payments equal to the index minus the strike multiplied by the value of animals covered by the individual's contract.

## Research Questions & Findings

As the promotion of index insurance as a financial tool for managing risk in developing countries continues to expand, it is imperative that researchers and policy makers understand its capacity to mitigate risk and the potential impacts of these insurance products on the poor. To date, there is little empirical evidence that these insurance products are benefiting poor households. The IBLI pilot in northern Kenya is a unique opportunity to extend the current knowledge on index insurance, to provide some of the first impact analysis of livestock insurance in a developing country context, and to begin to understand how the provision of insurance could play a role in assisting pastoralists in the horn of Africa.

This research is organized as three stand-alone papers, each focusing on one important factor that contributes to IBLI's overall potential for improving the livestock pastoralists. The remaining sections of this chapter provide a summary of the research question, relevant literature, and findings of each paper. It then closes with the limitations of this study and concluding remarks.

### *Chapter 2: What remaining risk do insured households face, and can the decomposition of this basis risk provide direction on improving the product?*

Basis risk is often cited as a drawback of index insurance products. The majority of research on basis risk involves crop insurance or weather derivatives in North America (e.g., Miranda 1991, Vedenov & Barnett 2004, Woodard & Garcia 2008). These studies tell us that weather index products can be a useful tool for mitigating risk even though policy holders continue to face risk. This research paper extends this literature to the developing world, examining the basis risk associated with IBLI in northern Kenya. We find that insuring with IBLI reduces variance in livestock survival rate for 35% of households but that an analysis over time provides evidence that the vast majority of households would increase utility by always purchasing full insurance even at unsubsidized and loaded premium rates.

A second focus of this paper is to determine which factors contribute to basis risk and thus the usefulness of the IBLI product. We examine design and idiosyncratic components separately. Design risk is shared by all households in the same geographic division while idiosyncratic risk is due to within division variation among households. We find that less than 10% of basis risk is due to design risk but that this remaining covariate risk would be difficult to capture with the existing index because the majority of basis risk is composed of idiosyncratic losses. Reducing the size of the index regions transfers some of the idiosyncratic losses to the covariate domain but also reveals that in some sublocations there is very little covariate risk. Households with fewer dependents and those that are highly dependent on livestock for their income experience less idiosyncratic risk, even after controlling for unobserved local fixed effects. But, the full set of observed household characteristics and location-fixed effects can capture very little of the idiosyncratic risk. It seems that for these pastoralists much of the risk that they face is due to random idiosyncratic losses not amenable to any sort of index insurance product.

This paper provides evidence that IBLI reduces the risk faced by a large portion of households, but that those benefits are perhaps smaller than some might hope or believe. Reducing the covariate region is one promising approach for increasing the coverage provided by IBLI, but there is a substantial population for whom risk is not easily linked to any apparent covariate region. For those households an index product is often not appropriate.

***Chapter 3: What are the key factors that determine household level demand for IBLI?***

In order for IBLI to be an effective product, we must understand the drivers of adoption and the remaining barriers for those who do not adopt. This research exploits a rich longitudinal household dataset to analyze household uptake of IBLI in the Marsabit region of northern Kenya. Because the survey includes detailed data on household herds and livestock mortality, this research is uniquely able to include data on insurable losses and basis risk in its analysis. The paper begins by examining those factors that have been found to be important for crop insurance demand and then focuses on the role of basis risk and spatiotemporal adverse selection.

Consistent with existing studies on demand for index insurance in developing countries, we find that demand is price sensitive but inelastic, liquidity constrained, and related to social connectedness (Cole et al. 2012; Giné, Townsend & Vickery 2010; Karlan et al. 2012; Mobarak & Rosenzweig 2012). We then go beyond the scope of those prior studies to explore the hypotheses that basis risk affects demand for IBLI and that spatial and/or intertemporal adverse selection exists due to how insurers price index products across space and time.

Basis risk—the difference between a policy holder's stochastic experience and the index—is one consequence of index-based insurance contracts. Because basis risk can result in uninsured losses (and gains), it limits the capacity of index insurance to fully smooth income. A number of recent studies include a proxy for basis risk in their analyses of index insurance, finding that increased basis risk does reduce uptake of the insurance product (e.g., Giné, Townsend &

Vickery 2008; Mobarak & Rosenzweig 2012).[3] To date, however, no study has been able to incorporate a direct measure of basis risk, much less basis risk decomposed into (correctable) design error and (uncorrectable) idiosyncratic risk.

We find that design risk, or the difference between the index and the insured covariate risk, has a negative and significant impact on uptake except for those facing the lowest premium rates. In addition, greater idiosyncratic risk, or the uninsured household-level variation in livestock mortality rates, has a negative and significant impact on level of demand among those that have experienced an exogenous increase in product understanding.

In addition, we examine demand for evidence of spatiotemporal adverse selection, a likely but often overlooked factor in demand for index products. Such behavior can be the result of premium levels that do not reflect variation in index quality, preseason information on changes to outcome distributions, or variation in expected indemnity payments. For example, ecological conditions during the sales window may provide information on the likelihood of an atypical season. In the case of IBLI, droughts leading to high livestock mortality are often the result of multiple seasons of poor precipitation. Although the index takes the previous season's conditions into account when estimating livestock mortality, the price of the policy does not change to reflect seasonal changes to risk.

We find evidence that households in divisions with greater idiosyncratic risk (lower correlation between individual and covariate losses and greater variance in losses) are less likely to purchase

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[3] Mobarak and Rosenzweig (2012) use perceived distance between the household and the nearest rain gauge that is used to calculate the index. Giné, Townsend, and Vickery (2008) also use perceived distance to rain gauge but include the percentage of crops that are castor or groundnut, the two crops for which the contracts were written.

insurance coverage, and that purchasing households buy less coverage before seasons that they expect to be better than normal (rather than normal or poor). These findings are consistent with the existence of spatiotemporal adverse selection and raise questions about the commercial sustainability of the product.

Our results are the first to use consumer level data to confirm that basis risk is indeed a significant factor in demand. Unfortunately, we find that idiosyncratic risk, which is beyond the scope of index insurance, contributes to low demand to a much greater degree than design risk, which could be addressed with an improved index. In addition, spatiotemporal adverse selection appears to be significant, which represents a cost that index insurance providers will need to account for when setting premium rates.

***Chapter 4: What impact does IBLI coverage have on the production strategies and welfare of pastoralist households? How do those outcomes compare to the outcomes of an unconditional cash transfer program in the area?***

The objective of the third research paper is to gain a better understanding of whether insurance helps pastoralist households increase their welfare as well as how those increases compare to other available policy interventions. To do this, we examine the impacts that IBLI has had on households in the Marsabit region in northern Kenya and compare them to those of the Hunger Safety Net Program (HSNP), an unconditional cash transfer intervention that came online in the Marsabit region at nearly the same time that IBLI became available there.

IBLI is a privately provided financial tool, built on public research, meant to be commercially sustainable. If correctly implemented, it provides pastoralists with the opportunity to reduce the impact of shocks, smoothing income and allowing households to maintain their productive capital. There is some evidence that formal insurance increases the use of higher-risk, higher-expected yield production methods (Hill & Viceisza 2010; Mobarak & Rosenzweig 2012) and that informal insurance can increase the benefits of formal insurance that has basis risk (Mobarak & Rosenzweig 2012). Yet, there is little empirical evidence of the welfare impacts of index insurance on rural households in developing countries (Miranda & Farrin 2012). In fact, some research indicates that those that could benefit the most from index insurance may be the least likely to purchase it (Binswanger-Mkhize 2012; Chantarat et al. 2010). Furthermore, IBLI supports pastoralist livelihoods but does not directly work towards opening up other economic opportunities. If continued pastoralism is either not preferred or vulnerable for reasons other than climate shocks, IBLI may provide a perverse incentive to remain in pastoralism.

In comparison, HSNP transfers are targeted specifically at the poor while IBLI is open to all. The theoretical case for cash transfers is that "low and variable income is central to the problem" of poverty (Arnold 2011, p.i). If poor households are currently unable to move out of poverty due to a basic lack of income, predictable, regular transfers may provide them with new livelihood opportunities, helping them invest in productive activities and escape poverty. But, if risk associated with climate shocks is a dominant force in household welfare, transfers may do very little beyond maintaining access to basic needs for the poorest. HSNP transfers provide a reference point for the region, illustrating the impact that a large (£80 million), targeted, public safety net can have on households.

Both programs should reduce relative uncertainty in future income, IBLI by making payments during droughts and HSNP by guaranteeing a minimum income. That being said, the two programs have very different approaches that may conflict with or complement each other. Because the HSNP transfers and IBLI are active simultaneously in the same region and are both included in the IBLI longitudinal household survey, this is an excellent opportunity to compare the impacts of IBLI with those of a publicly provided unconditional cash transfer program while searching for complementary or redundant outcomes.

We find that IBLI coverage reduces herd size, increases investments in existing productive capital through expenditures on veterinary services for livestock, increases in livestock productivity (as measured in value of milk production per TLU), and a subsequent increase in income from milk. Furthermore, IBLI coverage increases the sales of livestock, but only in periods that are not associated with high individual or covariate livestock mortality. Reduced exposure to risk appears to allow households to reduce precautionary savings in livestock, leading to greater investments in and productivity of the remaining herd.

HSNP participation increases the likelihood of household mobility, a key production strategy for maintaining large herds, and longer term participation increases reduces livestock mortality rate. Both of these impacts are especially relevant for poor households in northern Kenya where livestock mortality, mobility, and poverty are so tightly linked. There is also evidence that extended HSNP participation increases livestock milk productivity.

Considering the two programs simultaneously finds little evidence that the two programs interact, either as complements or as substitutes. Indeed, it seems that there is little overlap between the targeted HSNP participants (the elderly, needy, and households with more dependents) and those that are purchasing IBLI.

Comparing the benefits of the two programs normalized by their costs reveals that the HSNP program has much lower total program costs per unit benefit per client while IBLI has much lower marginal costs of an additional client per unit benefit. These findings highlight the high startup costs of creating and marketing a new insurance product, and that once the initial investment has been made, the public costs of continued premium supports for such an insurance program are very low for the benefits that they produce.

### Limitations

This study looks at the demand for and impact of a novel index-based livestock insurance product in its initial years. Pastoralists in northern Kenya and southern Ethiopia, to which the insurance product pilot has been expanded, have very little insurance of any kind and no experience with livestock insurance. Furthermore, the private firms offering insurance policies had no prior experience with this population or with an NDVI based index product. As households gain familiarity with the product and the providers become more adept at meeting the needs of their consumers, households may incorporate IBLI into their production plans in ways not reflected in these initial years. Education programs meant to increase uptake most likely increased the pace of these processes, but as insurance becomes the norm for the region, herding practices and behaviors that this study tested for may become more socially acceptable and thus become more prominent. We also expect that as households become more familiar with their own basis risk, they will change their demand and herding patterns in directions not anticipated by this study either in response to insurance or due to the index's role in providing information about predicted average losses.

A second limitation of this study is that it does not analyze the long term potential viability of either the IBLI product or HSNP transfers. The IBLI product is designed to be a commercially sustainable product, but has yet to make the transition away from the donor subsidies intended to get it off the ground. Certainly the initial HSNP was designed to have an end date, yet it is part of a much larger social safety net program which will likely continue providing transfers at some level while requiring complete public financing. Independent of the findings here, it is not possible to know which program will last beyond the pilot stage and what are the net welfare benefits over the lifetime of each program.

## Summary

In light of the excitement surrounding the opportunities for index insurance to reduce the risk faced by agricultural households that do not currently have access to insurance, our findings that basis risk is large even in what appears to be an ideal situation, provides a cautionary tale. Patterns in IBLI uptake confirms the importance of basis risk, driving demand down among those who understand the product and introducing spatiotemporal adverse selection as households demand responds to the current conditions and design risk. Nonetheless, analysis of downside risk shows that there may be net benefits of insuring with IBLI for the majority of households. Analysis of net benefits by way of observed household characteristics is less definitive. Consistent with findings of other index products, we find increased investments in productivity associated with insurance coverage and resulting increased value of production, but those activities have yet to express themselves in common indicators of welfare.

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# Chapter 2: Basis Risk and the Welfare Gains from Index Insurance

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## Introduction

Where insurance providers lack access to accurate, historic individual-level data, monitoring behavior is difficult, and/or claims validation is costly, conventional loss indemnity insurance is often cost prohibitive and thus inaccessible to consumers. These barriers exist and are exacerbated in the context of smallholder farmers and herders in developing countries that demand relatively small policies. One alternative to conventional policies—which provide indemnity payments based on verified individual losses—is to offer policies that provide indemnity payments based on some index related to average losses among groups of consumers. Such covariate level insurance products eliminate the need to price polices at the individual level and reduce the costs of validating claims by using data on average, rather than individual, losses. In addition, as group size increases, the potential for moral hazard and the costs of monitoring for such behavior fall. In cases where an easily observed exogenous signal of covariate losses is available, index insurance policies can further reduce costs of estimating average losses and reduce the negative impacts of cross-sectional adverse selection and moral hazard on insurer profits.

Basis risk, or the risk to which an insured individual is still exposed, has been called "the most serious obstacle to the effectiveness of weather index insurance as a general agricultural risk management tool" (Miranda & Farrin 2012, p.48). Basis risk has been studied quite extensively within the agricultural finance and insurance literature in the context of index insurance (or weather derivatives) for crops in developed economies (e.g., Miranda 1991; Turvey 2001; Vedenov & Barnett 2004; Woodard & Garcia 2008). This research establishes that even though basis risk is often significant, index products can none the less offer a valuable tool for cost effectively mitigating exposure to yield risk.

Recent years have seen a surge in the promotion and piloting of index insurance projects for agricultural households in developing countries. For example, in 2009 the International Finance Corporation and the World Bank jointly implemented the Global Index Insurance Facility (GIIF) to help grow and support index based insurance products in developing countries. By 2012, the GIIF was supporting projects insuring 228,000 clients for $USD 50.7 million in prospective indemnity payments (Global Index Insurance Facility, 2013). Unfortunately, most pilot projects have met with extremely low demand, even when premiums have been subsidized and extension efforts have been included. Basis risk is often cited as a likely cause of low demand (e.g., Hazell & Hess 2010; Miranda & Farrin 2012; Smith & Watts 2009) but the magnitude of this basis risk remains unknown.

To date, none of the studies associated with index insurance products in developing countries offer household—level estimates of basis risk. In fact, few studies explicitly include any measure of basis risk in their analysis at all. The lack of empirical attention to basis risk is especially disturbing because without it, there is no guarantee that index insurance is risk reducing. In cases where an individual's idiosyncratic risk is high or if the index is inaccurate, index products can represent a risk increasing gamble rather than the risk reducing insurance they are advertised to offer. Discerning the magnitude and distribution of basis risk should be of utmost importance for organizations promoting index insurance products, lest they inadvertently peddle lottery tickets under an insurance label.

The dearth of empirical estimates of basis risk in developing countries has multiple reasons. First, longitudinal household data are required in order to identify the distribution of basis risk. Because administrative cost savings due to reduced data collection are a key selling point of index insurance, such data are commonly lacking. In addition, premiums are usually calculated using the expected indemnity rate of the index (rather than on observed household losses) and insurers face little risk from moral hazard, so there is little profit incentive to collect individual-level verification data.[1]

Second, because there are multiple measures of basis risk, it is not obvious which metric is most salient to potential consumers or to which aspects of basis risk insurance providers should pay most attention. For example, a high loss event with no indemnity payment is often cited as a worst case scenario for policy holders. Although these "false negatives" are likely to have a negative impact on the reputation of the product, false negatives may be due to idiosyncratic losses which contractually fall outside of the product's coverage. Even in the event of a covariate false negative (when average losses are above the strike but the index remains below), individuals may be better off than in an alternative situation where indemnity payments were made, but losses were grossly under-estimated during extremely high loss events. To complicate matters further, indemnity payments may improve the net expected outcome while increasing its variance by over-estimating (over-indemnifying) losses. Such events reduce the usefulness of mean-variance analysis, a method commonly used to examine risky choices.

Third, most index insurance policies use an index measured in units fundamentally different from the ultimate object of insurance, as in the case of weather insurance contracts that aim to insure against crop loss, significantly complicating the estimation of basis risk. Several authors have used clever approaches to approximate the impact of basis risk in the absence of direct basis risk estimates. Mobarak and Rosenzweig (2012) exploit the likely reduction in correlation between precipitation in two locations as the distance between the two increases, using perceived distance to rain gauge as a proxy for perceived basis risk. This perceived distance measure is intuitively sound but requires that rain gauges correctly identify delayed monsoon onset (the insured risk) at their location and assumes that precision falls (basis risk increases) linearly and symmetrically with distance from the rain gauge. Giné, Townsend and Vichery (2008) use the

[1] The simplest method for determining actuarial premiums is to calculate the expected indemnity payment. This "burn rate" approach to pricing requires information on the average losses within product area but not on cross-sectional heterogeneity within the area.

proportion of a household's cultivated land that is planted with either castor or groundnut crops, the species used to generate the insurance policy parameters, as a proxy for basis risk. In theory, precipitation triggers set by the policy best reflect risks for groundnut and castor crops, while other crops' vulnerabilities are correlated with the index to a lesser degree. In that case, basis risk should increase as the proportion of planted caster and groundnuts falls. Both studies find that basis risk has a statistically significant and negative impact on farmers' demand for insurance, but the use of proxies make it difficult to assess the magnitude of basis risk.

In Hill, Robles and Cebellos (2013), distance to weather station is used as proxy for basis risk. They find that price sensitivity increases near the weather stations, where basis risk is presumed lower. Using that basis risk proxy as an indicator of product quality, they estimate that demand for higher quality products is more price sensitive than demand for low quality products. One interpretation of these findings is that high quality index products are normal goods, and that low price elasticity of demand may be a signal of poor index quality. This interesting finding begins to unpack the relationship between quality of the product and demand, an extremely relevant topic for insurance providers as they develop strategies aimed at increasing demand.

Other papers have used simulations and/or aggregate-level data to examine basis risk (e.g., Breustedt, Bokusheva & Heidelback 2008; Elabed et al. 2013; Leblois, Quirion & Sultan 2014; Norton, Turvey & Osgood 2012). Again, basis risk is consistently identified as significant and large with respect to existing risk portfolios but little can be said about the relative magnitude and distribution of basis risk among households. Although basis risk is widely acknowledged as a potentially serious issue as interest in index insurance has exploded globally, it remains remarkably under-researched.

The Index Based Livestock Insurance (IBLI) product was developed and commercially piloted among pastoralists in the Marsabit region of northern Kenya in 2010 (Chantarat et al. 2013). The IBLI index predicts livestock mortality rates using an innovative response function that was generated econometrically using historical data on household herd losses specifically with the objective of minimizing basis risk. IBLI has won a variety of international prizes for excellence in design and outreach, and attracted considerable international press (see http://livestockinsurance.wordpress.com/ for details). If basis risk significantly limits the benefits from IBLI, one might naturally wonder whether other products, not designed to minimize basis risk and less celebrated than IBLI, might suffer similar shortcomings.

Because the IBLI index is measured in the same units as the insurable household losses, it (perhaps uniquely) allows for direct estimation of the magnitude and cross-sectional heterogeneity of basis risk. This paper uses a four-year household panel dataset, which includes eight distinct semi-annual seasons of index values and household-level loss data, in order to examine the magnitude and components of basis risk that pastoralists face with respect to IBLI. Using the mean-variance approach that is often used to study index insurance in developed economies, we find that at unsubsidized and loaded premium rates IBLI significantly increases variance in livestock survival rates by an average of 4% but increases skewness in survival rates by 44% (from -1.15 to -0.65) among this pastoralist population. Restricting analysis to downside risk beyond the strike increases the ratio of households that benefit from IBLI and illustrates the vital role that premium rates play in determining the benefits of insurance. We then simulate the median willingness to pay rate, which is greater than the expected IBLI indemnity payments and loaded unsubsidized premium rates.

We then extend the literature on basis risk by examining the components of basis risk and the factors that contribute to their heterogeneity. The average household portfolio of downside risk is a composite of 27.2% covariate risk and 72.8% idiosyncratic risk. IBLI coverage successfully indemnifies 59% of the downside covariate risk that the average household faces. By design it can do nothing about idiosyncratic risk.

Examining covariate risk at various scales reveals considerable geographic heterogeneity. Covariate shocks represent only a small portion of households' risk portfolio in some locations, while in others the majority of livestock mortality is due to covariate shocks. The degree of geographic heterogeneity in the relative importance of covariate shocks points towards regions where IBLI may not offer an appropriate approach for reducing risk associated with livestock mortality. The idiosyncratic risk that households with index insurance continue to face is mostly the result of random unobserved household characteristics and events, but is also positively associated with a higher household dependency ratio and income diversification away from livestock-related activities, both of which likely reflect reduced managerial attention to animal husbandry, as well as geographic location.

This paper links the established work on agricultural index insurance products in higher income economies with the emerging literature on index insurance in developing economies while also providing a benchmark for basis risk that is useful for other index products. More broadly, it underscores the dangers of assuming that cleverly designed financial instruments perform as advertised. Given the considerable uninsured risk exposure faced by low-income rural households in the developing world, designing, implementing and evaluating risk management tools is a task of first order importance.

The rest of the paper is structured as follows. We begin with an examination of the components of basis risk in Section 2. Section 3 describes the context, the IBLI product, and data. Section 4 uses stochastic dominance, mean-variance and utility analysis to examine IBLI's impact on the distribution of outcomes that insured households face. Section 5 decomposes basis risk into its various components in order to reveal which factors drive the product's imperfect performance and which are associated with idiosyncratic losses. We conclude in Section 6 with a discussion of the implications of our findings for IBLI and other index insurance products. Given the burgeoning interest in index insurance within the development, finance, and agricultural communities, and the glaring dearth of evidence on basis risk in these products, our findings offer a cautionary tale to researchers and practitioners alike.

## Basis Risk

Households with index insurance face two potential sources of basis risk: design risk due to differences between the index and the actual covariate risk it is meant to mimic, and idiosyncratic risk resulting from heterogeneity among individuals' losses within the same index region.[2] Design risk results from imperfect index design. Idiosyncratic risk falls outside the scope of an index policy. It is an artifact of generalizing information and can only be changed by adjusting the scale of the index region.[3] This section develops a framework for decomposing basis risk into its idiosyncratic and design components before we examine them individually.

As a stylized example, let individual $i$ living in a spatially defined division $d$ experience losses in period $t$ at rate $L_{i,d,t}$.[4,5] Large scale events such as drought or floods can generate losses across many individuals in the same area. Such covariate losses are reflected in $\bar{L}_{d,t}$, the average or covariate losses in area $d$ at time $t$. An individual's losses can then be divided into covariate losses and a remaining idiosyncratic component $(L_{i,d,t} - \bar{L}_{d,t})$.

[2] It is possible that there are multiple sources of covariate risk that may themselves be uncorrelated. In those cases, an index insurance policy may provide coverage for only one such covariate risk or an aggregate of the covariate risks. But, sources of agricultural risk are often correlated. For example, livestock mortality from disease is likely correlated with mortality due to drought. In the case of IBLI, the policy index is predicted livestock mortality rate, and was constructed using data that included all reported causes of death.

[3] There is likely a trade-off between scale and data requirements so that reducing design risk by increasing scale is likely to require more data lest the quality of the index suffer. Moreover, the finer the scale, the greater the chance for asymmetric information problems associated with adverse selection and moral hazard to reemerge as problems. There may therefore be an optimal scale-quality optimum that is a function of spatial correlation of insured losses and the cost of data collection.

[4] A division could be defined any number of ways. Defining index divisions spatially makes sense for products that hope to mitigate risk associated with weather-sensitive activities, such as agriculture, where losses are often spatially correlated.

[5] For consistency with IBLI and comparability with conventional insurance, where indemnity payments are based on individual losses, we assume an index that predicts loss rates. This discussion can easily be recast in terms of deviations from any value, such as precipitation below a benchmark or number of cooling days.

The variance in loss rate that an individual faces over time ($Var_t[L_{i,d,t}]$) is one metric of risk.[6] Similar to loss rate, an individual's risk can be decomposed into a covariate component, an idiosyncratic component, and the covariance between idiosyncratic losses and covariate losses ($Var_t[L_{i,d,t}] = Var_t[L_{i,d,t} - \bar{L}_{d,t}] + Var_t[\bar{L}_{d,t}] + 2 * cov_t[L_{i,d,t} - \bar{L}_{d,t}, \bar{L}_{d,t}]$). As $L_{i,d,t} \to \bar{L}_{d,t}, Var_t[L_{i,d,t}] \to Var_t[L_{i,d,t}]$. Alternatively, households that typically experience much less risk than their neighbors face idiosyncratic risk that is larger than their total risk because the idiosyncratic and covariate components negatively covary.[7] This points towards a potential population for whom a financial tool designed to indemnify covariate risk may be inappropriate because it would increase the variance of losses.

Let an insurance product be available that makes indemnity payments based on the values of an index generated in each division at every period ($Index_{d,t}$). The difference between experienced losses and the index ($L_{i,d,t} - Index_{d,t}$) is basis error. The variance of basis error, often called basis risk and shown in Equation (1), is the risk that an insured individual faces.

$$(1) \qquad Var_t[L_{i,d,t} - Index_{d,t}] = Var_t[L_{i,d,t}] + Var_t[Index_{d,t}] - 2 * Cov[L_{i,d,t}, Index_{d,t}]$$

So long as the variance introduced by the index is less than twice the covariance between the index and losses, an individual can reduce risk by purchasing the index insurance.

An index that tracks average division level losses exactly maximizes total coverage and minimizes basis

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[6] Assume that variance is a suitable measurement of risk for the time being. We will extend this analysis to allow for asymmetric preferences by examining skewness and semi-variance after decomposing basis risk.

[7] Perhaps a more intuitive specification of the covariate risk faced by an individual is limited to that risk which positively co-varies with their division average and has a maximum value of the individual's total risk. In this case, idiosyncratic losses are limited to those individual losses that are greater than division average losses, and covariate risk is calculated using only that portion of division losses that are not greater than individual losses. The drawback to this alternative specification is that it does not capture variance associated with overestimation of losses such as those falling into the false positive region, as will soon be discussed.

risk but is likely to be unachievable or at least generally not cost effective.[8] Differences between the division average and the index are called design errors. The variance in design error, design risk ($Var_t[\bar{L}_{d,t} - Index_{d,t}]$), is the remaining covariate risk that could theoretically be captured by a (better) division level index.

The risk that an insured individual faces can be described by the sum of design risk, idiosyncratic risk, and the covariance between design error and idiosyncratic error (Equation 2).

$$(2) \qquad Var_t[L_{i,d,t} - Index_{d,t}] = Var_t[\bar{L}_{d,t} - Index_{d,t}] + Var_t[L_{i,d,t} - \bar{L}_{d,t}] + 2Cov[L_{i,d,t} - \bar{L}_{d,t}, \bar{L}_{d,t} - Index_{d,t}]$$

In addition to the magnitude of basis risk, the sign and circumstances of basis error are also likely to be important to consumers. Figure 1 illustrates that point by displaying all of the possible loss-index combinations. The vertical and horizontal axis represent the range of time-specific individual losses ($L_{i,d,t}$) and index values ($Index_{d,t}$), respectively, where both index and losses refer to a loss rate ($L_{i,d,t}, Index_{d,t} \in [0,1]$ ). The 45° line represents the set of outcomes where the index and losses are identical and basis error is zero. Above the 45° line, losses are greater than those predicted by the index, while below the 45° line, the index predicts higher losses than experienced. The absolute difference between the index and experience increases as one moves away from the 45° line, so that basis errors are largest in the top left and lower right corners.

Contracts may map index values onto indemnity payments in a nonlinear fashion. For example, index insurance generally does not cover all losses. The strike ($S$ in Figure 1) is the value that the index must

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[8] If basis risk is the variance of the remainder generated by subtracting index values from individual losses ($\varepsilon_{i,d,t} = L_{i,d,t} - Index_{d,t}$), then basis risk is minimized by using an index perfectly identical to the division average losses. Or $arg \min_{Index_{d,t}} Var_{i,t}[L_{i,d,t} - Index_{d,t}] = arg \min_{Index_{d,t}} Var_{i,t}[\varepsilon_{i,d,t}] = Index_{d,t}{}^*$, such that $Index_{d,t}{}^* = \bar{L}_{d,t}$.

exceed in order for there to be an indemnity payment. If the index falls below the contractually specified strike level, no payments are made even if positive losses are predicted. If the index is greater than the strike, payments are made according to the conditions of the contract. The lower left shaded section represents those outcomes where both losses and the index are below the strike. Although events falling into this region may provide a signal as to the relationship between the index and events, it does not impact the contract's precision in providing accurate indemnity payments because the contract explicitly does not cover risk in this region.

Events during which high losses are suffered but the index remains below the strike level are termed false negatives. Events falling into the false negative region are likely to have a poor impact on the reputation of the product because households pay a premium and experience losses that exceed the strike, but none of those losses are indemnified. Even if the index falls directly below the strike, from the perspective of a consumer the index might as well be zero. Analogously, a high index that initiates a payment while the individual losses are less than the strike falls in the false positive region. Although false positive indemnity payments are a windfall for individuals, the payments are not necessarily risk reducing and may perversely transfer money from low to high income states through premiums to fund that windfall. For actuarial products, transfers to high income states necessarily require transfers out during low income states, increasing the downside risk that households face. The basis risk faced by an individual would describe the distribution of $(L_{i,d,t}, Index_{d,t})$ realizations scattered in Figure 1, with variance as described by Equation (1).

Regression analysis provides one method for examining basis error patterns across index levels. Examining only design risk for a moment, Equation (3) expresses division level average losses as a function of the index.

(3) $$\bar{L}_{d,t} = \alpha_d + \delta_d Index_{d,t} + \mu_{d,t}$$

$$E[\mu_{d,t}] = 0$$

Here $\alpha_d$ is the intercept, $\delta_d$ is the expected change to covariate losses for a unit change in the index, and $\mu_{d,t}$ is mean zero error.[9] Together $\alpha_d, \delta_d$ tell us the expected design error for any index value. The variance of the error informs on the uncertainty around the expectation. Notice that the variance of the error term ($Var_t[\bar{L}_{d,t} - \delta_d Index_{d,t}]$) is similar but not equivalent to our earlier definition of design risk ($Var_t[\bar{L}_{d,t} - Index_{d,t}]$) unless $\delta_d = 1$.

An index without design error will have coefficients $\alpha_d = 0, \delta_d = 1$ and $Var[\mu_{d,t}] = 0$. Deviations from this zero design risk ideal can manifest in a number of ways. For example, if $\alpha_d < 0$ and $\delta_d \approx 1 - \frac{\alpha_d}{S}$ where $S$ is the strike, then the index generally over predicts losses below the strike and under predicts losses above the strike. Perhaps most usefully, if Equation (3) is estimated and $\widehat{\alpha_d} \neq 0$ or $\widehat{\delta_d} \neq 1$ basis risk could be reduced by transforming the existing index ($Index_{d,t}$) to a new index ${Index_{d,t}}^*$, where ${Index_{d,t}}^* = \alpha_d + \delta_d Index_{d,t}$.

Individual losses can be similarly expressed as a function of division level covariate losses and idiosyncratic losses. Equation 4 expresses that relationship as the sum of an intercept ( $\tau_{i,d}$), a parameter ($\rho_{i,d}$) times covariate losses, and an idiosyncratic component ($\vartheta_{i,d,t}$).

(4) $$L_{i,d,t} = \tau_{i,d} + \rho_{i,d}\bar{L}_{d,t} + \vartheta_{i,d,t}$$

$$E[\vartheta_{i,d,t}] = 0$$

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[9] We assume stationarity of losses and the relationship between individuals, divisions and the index. Nonstationarity could be modeled by allowing coefficients $\alpha_d$ and $\delta_d$ to vary with time but adds little to this discussion.

The risk described by $Var_t[\bar{L}_{d,t}(\rho_{i,d}-1)+\vartheta_{i,d,t}]$ is individual level losses that could be insured by a loss indemnity insurance product but is not, by design, covered by an index product.[10] It represents the minimum possible risk that an individual could be exposed to after purchasing an index insurance product based on $\bar{L}_{d,t}$. Index insurance is ideal for individuals with $\tau_{i,d}$ near zero, $\rho_{i,d}$ near one, and a low level of idiosyncratic losses.

The relationships illustrated in Equations (3) and (4) can be combined to express the relationship between individual losses and the index (Equation 5). Notice that the basis error parameters can be divided into division level components (design error) and individual level components (idiosyncratic error).

(5)
$$L_{i,d,t} = \beta^0_{i,d} + \beta^1_{i,d} Index_{d,t} + \varepsilon_{i,d,t}$$

Where:

$$\begin{aligned} \beta^0_{i,d} &= \alpha_d + \{\tau_{i,d} + \alpha_d(\rho_{i,d}-1)\} \\ \beta^1_{i,d} &= \rho_{i,d}\delta_d \\ \varepsilon_{i,d,t} &= \mu_{d,t} + \{\vartheta_{i,d,t} + \mu_{d,t}(\rho_{i,d}-1)\} \end{aligned}$$

Equation 5 can be estimated using historic data to examine the components of basis risk at different index levels, in different divisions, and for individual households. Holding the parameters constant within divisions estimates the expected performance of the index product within each division. If the index perfectly predicts a household's experience, then $\beta^0_{i,d} = 0$, $\beta^1_{i,d} = 1$ and $\varepsilon_{i,d,t} = 0\ \forall t$.

***Welfare effects***

If insurance is priced to be actuarially fair and the level of risk is constant, purchasing insurance has no impact on expected outcomes and the immediate welfare impacts of insurance are captured by changes to variance. Once the actuarial fairness assumption is relaxed or if risk exposure is heterogeneous across individuals or over time, then determining the usefulness of a product is much less straightforward.

[10] Idiosyncratic risk can be calculated by $Var_t[L_{i,d,t}-\bar{L}_{d,t}] = Var_t[\bar{L}_{d,t}(\rho_{i,d}-1)+\vartheta_{i,d,t}]$. If $\rho_{i,d}=1, V[\vartheta_{i,d,t}]$ is equal to idiosyncratic risk.

Insurance may then have heterogonous impacts on both the mean and variance of outcome.

The stochastic dominance approach allows us to make some headway. Let an individual's distribution of demeaned insurable losses have a variance $Var_t[L_{i,d,t}]$. An actuarially fair, loss-indemnity insurance contract with no deductible reduces that variance to zero (by perfectly transferring assets from periods with no losses to periods with losses). An actuarially fair index insurance contract with no design risk or deductible leaves an insured individual only exposed to idiosyncratic risk. As long as $2 * Cov[L_{i,d,t}, \bar{L}_{d,t}] > Var_t[\bar{L}_{d,t}]$, then $V[L_{i,d,t} - \bar{L}_{d,t}] \leq V[L_{i,d,t}]$ and index insurance is variance reducing. That is, for individuals with sufficient covariate risk, actuarially fair index insurance with no design risk (at least) weakly second-order stochastically dominates no insurance.

But if we allow for design risk, there is no assurance that $Var_t[L_{i,d,t} - Index_{d,t}] \leq V[L_{i,d,t}]$ even when covariate risk is high. With high levels of design risk or high covariance between idiosyncratic losses and design error, it is feasible that purchasing index insurance increases risk. Thus, index insurance with the possibility of design risk does not necessarily weakly second order stochastically dominate the no insurance alternative even when covariate risk is high. A risk averse individual may prefer no insurance over index insurance with the possibility of design risk. Since design risk is practically inevitable, arguably even optimal given costly data collection, this makes the value of index insurance an intrinsically empirical question because there exist many contracts with design risk that could reduce risk. And, because the impact of design error on basis risk is not homogeneous, products may be risk increasing for some individuals while for others they are risk reducing. Put differently, index insurance with design error might be a targetable product. The welfare effect of index insurance contracts and the distributional profile of those effects among heterogeneous agents are thus inherently empirical questions. The existing literature has not yet explored these issues.

Once overhead costs (loadings) are included, even loss indemnity insurance can be stochastically dominated by a no insurance state. In fact, the extremely high cost of monitoring and verification has made loss indemnity insurance loadings so high that it is nearly impossible to provide in many situations, such as to smallholder farmers or pastoralists in remote locations. It is specifically this dilemma that index insurance attempts to address by providing low cost insurance based on exogenous indicators of covariate shocks and indemnity payment schedules that require little (or no) verification.

## Background on Kenyan Pastoralists, IBLI and the Data

Pastoralist households in northern Kenya depend on livestock for most of their income (mean =70% and median=100% in our data) as well as for a wide variety of financial and social services. Frequent droughts in the region play a large role in livestock mortality and household herd size. For example, in both 2009 and 2011, severe droughts hit the horn of Africa, causing mortality rates greater than 50% in some locations (OCHA 2011; USAID 2011; Zwaagstra et el. 2010). Indeed, drought is the single largest cause (47%) of livestock mortality in our survey data. For pastoralist households, herd loss represents a direct loss of wealth and productive assets.

The Index-Based Livestock Insurance (IBLI) pilot started in the Marsabit district of northern Kenya in January 2010. IBLI is an index insurance product based on a remotely collected indicator: the normalized difference vegetation index (NDVI). NDVI is an indicator of the level of photosynthetic activity in observed vegetation and, being a good proxy of the available rangeland forage for animals, should be highly correlated with livestock mortality.[11] The NDVI data originally employed was sourced from NASA's Advanced Very High Resolution Radiometer (AVHRR) NDVI3g sensor.[12] The IBLI contract was designed by regressing historic livestock mortality rates on transformations of lagged NDVI data to estimate a

[11] Purchased feed is essentially non-existent in these populations.

[12] The current IBLI product uses NASA's eMODIS dataset. See Vrieling et al. (2014) for analysis on selecting the best relevant NDVI source for IBLI and the intercalibration efforts to stitch the relatively new eMODIS dataset (available from 2000 to the present) with the AVHRR data (available from 1981 to 2012).

seasonal livestock mortality rate response to NDVI observations (Chantarat et al. 2013).[13] The regression approach is appealing because minimizing the residual sum of squared errors is equivalent to minimizing the variance of the difference between the index and individual losses, or basis risk.

Division-specific indices are calculated for each of Marsabit's five administrative divisions. The five divisions were grouped into two contract divisions, upper and lower, each with its own response function. Figure 2 displays the five index (administrative) divisions. The legend shows how the index divisions are allocated into contract divisions. The IBLI strike and deductible are set at 15% so that indemnity rates are equal to max(index-0.15,0).

The Marsabit region experiences a bimodal rainfall pattern, which naturally produces two insurance seasons per year. The long rain/long dry season (LRLD) begins (contractually) on March 1st and ends September 30th. The short rainy/short dry season (SRSD) begins October 1st and runs through end-February. Twelve month contracts are sold twice a year, during the two months preceding each insurance season (January-February and August-September), so that each twelve month contract covers two indemnity periods. See Chantarat et al. (2013) for more detailed information on the IBLI product.

This analysis uses data from a longitudinal household survey collected annually for four years between 2009 and 2012. The first survey round took place three months before IBLI launched and subsequent rounds took place during the same October-November period each year thereafter. The survey questionnaires were collected within 16 sublocations selected to provide a wide variety of market access, agro-ecological zones, ethnicity, and herd size. In order to maintain statistical power in an environment in which geographic clustering effects are likely large, the survey collected data from four of the five IBLI pilot divisions: Central/Gadamoji, Laisamis, Loiyangalani, and Maikona. North Horr was omitted. Within sublocations,

[13] The IBLI contract was revised for scale-up and implemented in Marsabit as well as Isiolo and Wajir districts, in August 2013 (see Woodard, Shee & Mude 2014 for more information). As this paper focuses on the years 2009 – 2012 the analysis is largely based on the IBLI design as specified in Chantarat et al. (2013).

households were randomly selected within herd size strata. The survey collects data on a wide variety of demographic, economic, and health characteristics but emphasizes livestock herd dynamics.

Because we are interested in comparing estimated sample variances, this analysis uses only those households that participated in all four rounds. Of the original 924 households in the survey, 832 were available for all four rounds. About 30 households (~3%) were replaced each round. Attrition, for the most part, was due either to the household moving to a distant location or unavailability of an appropriate household respondent. The first factor may be the result of shock or an indicator of household mobility, both of which are of interest in this study. Repeated visits were attempted to reduce the incidence of the second factor. Attrition analysis (not shown) finds that households that leave the survey tend to have fewer members, rely on livestock for a smaller portion of their income, and consume more per person.

We place the additional restriction that households have at least one animal in every round so that their livestock mortality rate is defined, reducing the sample further to 736 households. Those dropped due to periods with no livestock are similar to the exiting households with the addition of having more education and smaller herd sizes.[14]

Thus, our final sample is the product of attrition, due to households leaving the survey, and truncation as we study only those households that have livestock in every period. The result is a sample in which shocks are likely underrepresented. If attrition or reported zero livestock are due to livestock shocks, the sample selection process will bias shock related estimates (e.g., average livestock losses) downwards. Unfortunately, there is little that can be done to address this bias except to control for those variables known to be related to attrition or zero livestock, which we do.

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[14] See Appendix A for a full analysis of attrition/drop patterns and effects.

Consistent with the IBLI contracts, the months are grouped into two insurance seasons: LRLD and SRSD.[15] The ideal estimate of seasonal livestock mortality rate is the ratio of animals entering a season that die during the season. But the data do not allow for tracking specific animals through the season so we construct an alternative estimate of seasonal livestock mortality rate. The numerator of this alternative estimate is the sum of monthly losses ($M_{i,d,m}$) for individual $i$ in division $d$ during month $m$ for all months that fall into season $s$. The denominator is composed of the sum of the herd size at the beginning of the season ($H_{i,d,start}$) and all monthly additions to the herd over the following season ($\sum_{m\in s} A_{i,d,m}$).[16] Thus, seasonal livestock mortality rates ($L_{i,d,s}$) are estimated by dividing the season's cumulative livestock mortality by the total herd owned by household that season (Equation 6).[17]

(6)
$$L_{i,d,s} = \frac{\sum_{m\in s} M_{i,d,m}}{H_{i,d,start} + \sum_{m\in s} A_{i,d,m}}$$

*Where:*
$$s = \begin{Bmatrix} LRLD & if\ m = [March, \dots, Sept] \\ SRSD & if\ m = [Oct, \dots, Feb] \end{Bmatrix}$$

Average mortality rates vary widely between the four study divisions and across seasons (Figure 3). More important for this analysis, there is clear evidence of large covariate losses within divisions, as is revealed by seasons with high average mortality rates. IBLI can only be an effective risk mitigation tool if individual level catastrophic losses are correlated. An ideal IBLI product would indemnify those (average) losses that

[15] Each SRSD season runs from October through February, crossing into a new calendar year. They are dated by the year of the month that the season begins (October) rather than the year that the season ends (February). LRLD begins at the beginning of March and ends at the end of September so this is not an issue.
[16] $H_{i,d,start}$ is calculated using reported herd sizes at the time of the survey and iterating backwards, adjusting for monthly birth, death, purchase, sale, and slaughter. Herd size is constrained by $0 \leq H_{i,d,m}\ \forall\ i, d, m$ to address errors in recall that occasionally lead to erroneous negative livestock herd size estimates.
[17] We rely on estimates of livestock mortality rate because the data does not track individual livestock through each season. The qualitative results presented in this paper are robust to using an alternative method for calculating livestock mortality rate, which is described and used in Chantarat et al (2013).

are above the strike (0.15) in Figure 3.

Although IBLI coverage was only available for the last five of the eight insurance seasons captured in these data, all eight seasons are used in our analysis of basis risk in order to better estimate the basis risk distributions that households face (see Appendix B for index values). In the following sections we examine the benefits of IBLI and estimate a number of basis risk metrics in order to provide a clearer picture of IBLI's performance. We focus on full insurance so that net outcomes are directly comparable to the observed livestock survival rate.[18]

There are a number of relevant premium rates for IBLI. During the periods covered by these analyses, annual policies were sold at subsidized rates of about 3.325% and 5.5% in lower and upper regions, respectively. The within-sample actuarially fair premium rates (Central/Gadamoji=9.25%, Laisamis=7.5%, Loiyangalani=7.0%, and Maikona=12.25%) provide the best estimates, however, if the intent is to focus on the intertemporal smoothing effect of insurance. Finally, the unsubsidized loaded annual premium rates calculated by the insurance providers in 2014 (Central/Gadamoji=10.6%, Laisamis=11.3%, Loiyangalani=9.2%, and Maikona=10.7%) provide information on outcomes associated with commercially sustainable, unsubsidized premium rates. These final rates reflect a reevaluation of the expected indemnity payments in 2014 in response to severe conditions between 2009 and 2013. Notice that the premium rates are no longer common in the upper and lower contract divisions as of 2014.

All of the analysis that follows is performed using seasonal premium rates calculated as half the annual rate, although we continue to report annual premium rates so as to avoid confusion. Unless otherwise stated, our analysis focuses on outcomes associated with insurance sold at the commercially sustainable premium levels and thus provides a lower boundary for the impact that this insurance product would have had on

[18] At full insurance all calculations can be performed as a ratio of the full herd, as the net survival rate estimated by subtracting seasonal loss and premium rates from one, and adding indemnity rates when they exist.

households purchasing at the subsidized or actuarially fair premium rates.

## Aggregate Level Basis Risk

Because of basis risk, index insurance need not be mean preserving and may change the shape of the wealth distribution in any number of ways. In this section we compare the distribution of the net survival rates with and without insurance by testing for stochastic dominance, examining changes to moments, and finally by comparing estimated average utility over the survey periods. Net survival rate is defined as the seasonal survival rate in the uninsured case and as the seasonal survival rate, less premiums paid, plus any indemnity payments in the insured case. Unless stated otherwise, we use the loaded and unsubsidized premium rate to provide a lower bound on the benefits of IBLI. We find that index insurance with a positive probability of false negatives can never stochastically dominate purchasing no insurance but that fully insuring under IBLI improves the distribution of outcomes by reducing downside variance. Utility analysis under the maintained hypothesis of constant relative risk averse preferences finds that most households are better off purchasing full IBLI coverage at the provider estimated loaded premium rate than not purchasing; the benefits of purchasing insurance, however, appear small.

IBLI coverage changes the distribution of outcomes dramatically (Figure 4). Most apparent is a significant mass of households that experience a greater than one net outcome with insurance, when (by construction) there are no households with greater than one livestock survival rate.[19] Households with greater than one net survival rate received indemnity payments exceeding their losses plus the premium. Notice as well that a small number of observations moved to the left of zero livestock survival in the insured case. A less than zero net outcome is due to households paying premiums and suffering extremely high losses but receiving

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[19] That is not to say that there are not observations of net seasonal growth to herd size. Herd size increased between seasons in about 32% of the observations. Here, we are examining only the insured risk, which is livestock mortality, not changes to herd size.

very little or no indemnity payment.[20]

### *Stochastic Dominance*

Testing for stochastic dominance is one approach for ordering risky choices in a manner consistent with expected utility theory. The main advantage of the stochastic dominance approach is that is allows for ordering with few assumptions about the utility function. Unfortunately, with only eight seasonal observations per household, our data do not allow for powerful tests of stochastic dominance at the household level. Rather, we test for stochastic dominance at the population level.

Let *f(x)* describe the distribution of observed livestock survival rates and *g(x)* describe the net outcome of fully insuring (i.e., net of premium and indemnity payments). If the insured survival rate distribution first order stochastically dominates (FSD) the uninsured distribution, $F(x) \equiv \int_{-\infty}^{x} f(x)dx \gg G(x) \equiv \int_{-\infty}^{x} g(x)dx$, then the expected outcome with insurance is better than without insurance. Figure 5 shows that the insured distribution does not FSD the uninsured state. In particular, as shown in the right panel of Figure 5, no insurance dominates insurance when households experience extremely high losses and do not receive indemnity payments greater than the premium. Indeed, the insured distribution necessarily fails to stochastically dominate the uninsured case at any degree of stochastic dominance because of the positive probability of negative net survival rates under insurance due to catastrophic losses with little or no indemnity payment.

### *Mean and Variance Metrics*

The mean-variance method for analyzing choices under risk is common in the insurance literature. For example, Miranda (1991) defines the change to yield risk due to insurance as the variance in yield without

[20] In nine of the 5,704 observations, households experienced less than zero net livestock survival rate due to premium rates being added to an already high livestock mortality rates. The minimum net outcome is -0.0565.

insurance less the variance of the net yield, which includes premiums and indemnity payments. This approach is intuitive and requires the estimation of very few parameters, allowing for more powerful household level analysis than does testing for stochastic dominance, and is consistent with expected utility as long as mean and variance are sufficient for describing differences in outcomes (Meyer 1987). But insurance may lead to changes beyond those that are captured by mean and variance, so that mean—variance analysis is inconsistent with important classes of preferences. For example, risk averse individuals may distinguish asymmetrically between deviations from the mean due to extremely good outcomes and extremely poor outcomes (Alderfer & Bierman 1970). Agricultural insurance products specifically target those negative outcome events rather than all variation (Turvey 1992). Higher moments (beyond mean and variance) can be calculated to examine changes to distributions that are not symmetrical while semi-variance analysis examines changes to downside risk.

Loaded, unsubsidized insurance in unlikely to be mean preserving or improving, since it is priced above the actuarially fair level. Comparing the expected net outcome of being insured with the uninsured case shows that the loading indeed results in a net decrease in survival rates from about 86.0% to 84.7% for a difference of about 1.2% per season (Table 1), which is very near the estimated loading rate.[21]

But the primary motivation for purchasing insurance is presumably not to increase expected outcomes but to reduce the risk of extremely poor outcomes. In this case, the average variance with insurance is slightly greater than without. This is not surprising as the domain of potential outcomes has increased for insured households and we expect over-indemnification to also contribute to outcome variance. The histograms of outcomes (Figure 4) suggest that IBLI impacts the downside risk that households face via indemnity payments that shift outcomes to the right. Analysis of skewness supports that hypothesis. Distributions are

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[21] The loading rate is about 40% of the actuarial premium rate. One can back out the provider's estimated average actuarially fair premium rate by dividing the average seasonal premium (5.37%) by 1.4 which comes to about 3.83%. Thus the average loading is the difference between the two or about 1.5%

negatively skewed in both the uninsured and insured cases, but insurance significantly reduces the skewness magnitude, by 44.4% (t-stat=6.87, Table 1). The skewness values indicate that the impact of IBLI is not a symmetric contraction of the variance. Rather, IBLI reduces the likelihood of large shocks at a small cost to expected outcomes, as is to be expected from a loaded insurance product.

We now focus our attention on downside risk. By examining only risk associated with shocks producing greater than 15% livestock mortality, we reveal how IBLI performs in the domain that falls within the coverage parameters of the IBLI policy. To do so, we use an approach similar to that described in Turvey (1992). Downside risk is calculated by $\frac{1}{T-1}\sum_{t=1}^{T}(O_{it} - \dot{O}_t)^n I(Z_{it}))$ where $O_{it}$ is the outcome experienced by individual $i$ in time period $t$, $T = 1,2,\ldots,8$, $\dot{O}_t$ is the target, $n$ is the weight given to deviations from the target, and $I(Z_{it})$ is an indicator function that is equal to one if a condition is met and equal to zero otherwise. In this case, the outcome under examination is livestock mortality rate and the indicator function is used to identify severe events defined by those seasons in which the household experienced at least 15% livestock mortality.[22] The target is used to reference the magnitude of the shock, which we set to the strike in order to capture the risk beyond the strike, associated with those extreme losses. The outcome set of measures are the average sum of the distance between outcome and strike with distance weighted by $n$. Because the distance measure is not in relation to the mean, as it is with variance, the addition of a constant premium rate affects this measure of downside risk. This is important as risk coverage is often discussed quite separately from premium levels. To explore the effects of premium levels on downside risk we include estimates of downside risk for the subsidized, within-sample actuarially fair, and commercial, unsubsidized rates.

Setting $n = 1$ provides an estimate of the expected losses above the strike. The expectation of the outcome

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[22] The equation used to estimate downside risk includes a degree of freedom correction (T-1) because it is a transformation of variance, which can be consistently estimated by setting $\dot{O}_t$ to the mean of $O_{it}$, n to 2, and the indicator function to one.

will rest on the level of loading or subsidy applied to the premium and the timing of the indemnity payments. If indemnity payments are perfectly made during high loss events, households with insurance will experience an improvement to expected conditional losses at the actuarially fair premium rate. Conversely, if the product is not making payments during the high loss events we could see a reduction to expected survival even at subsidized rates. The estimates indicate the index is performing somewhere between the two boundary outcomes described above, triggering in the right seasons at least some of the time (Table 2).

Semi-variance around the target is estimated by setting $n = 2$. As with the conditional expected losses, the estimates indicate that the benefits associated with reductions to semi-variance during severe events are very sensitive to the premium levels (Table 2). At the loaded rate, the average household is worse off with IBLI than without it, but at the subsidized rate the opposite is true. It worth noting that perfect loss-indemnifying insurance above 15% would drive both the expected losses above 15% and the semi-variance above the strike to zero. But, perfect index insurance would not cover all losses above the strike unless all individuals within the covariate region sufferer from identical losses at all times. For example, 49.2% of the observations used in Table 2 (experiencing livestock mortality rate>0.15) occurred during periods when covariate losses were below 0.15, and thus fall outside the parameters of the IBLI contract. We will examine the index design and idiosyncratic contributions towards this remaining basis risk, represented by the semi-variance here, in Section 5.

On average, IBLI significantly reduces expected net survival rate but also adjusts the distribution to one more favorable to the household as indicated by a reduction in skewness. Restricting our analysis to those periods when households experience greater that 15% livestock mortality reveals that the benefits of IBLI coverage are highly sensitive to the premium rates. Yet, the impact of IBLI is likely to be heterogeneous across loss rates and households, so that while many households do benefit from IBLI, some do not.

Table 3 reports the share of households for whom IBLI improves survival rates, variance, skewness or semi-variance in order to begin unpacking the distribution of benefits/cost. At the division level, the loaded unsubsidized premium rates exceed the expected IBLI indemnity payments in all divisions but Maikona where the expected seasonal indemnity payment rate=6.1% and premium rate=5.6%. Using only the mean standard, those 226 households in Maikona are better off with IBLI than without. At the subsidized rate, all households realize improved expected outcomes with IBLI.

Assuming that the motive for purchasing IBLI is to reduce (downside) risk, higher moments are more important metrics. Variance is reduced for 34.6% of the population, skewness is reduced for 81.8%, and downside risk is improved for 35.4% and 59.5% at the unsubsidized and subsidized rates, respectively. At either premium level, many of these households experience net benefits in one metric and net costs in another. The mean variance framework cannot order outcomes for these households.

***Utility Analysis***

Utility analysis allows us to order the outcomes for all the households but requires specific assumptions about households' preferences. Following other work on the utility gains from insurance (e.g., Woodard et al. 2012), we assume constant relative risk aversion (CRRA) such that utility is of form $U(x_{idt}) = \frac{(x_{idt})^{(1-R_i)}}{(1-R_i)}$, where $x_{idt}$ is herd size held by household $i$ in IBLI contract division $d$ at period $t$, and with Arrow-Pratt absolute risk aversion $R_i$.[23] CRRA utility has been shown to provide a good fit to the risk preferences of individuals so long as the scale of risk (payoffs) does not change drastically (Holt & Laury 2002). In this case, the scale of risk is defined by changes to herd size due to losses, which are rarely more than a factor of ten.[24]

To simulate being fully insured by IBLI, we begin by calculating the observed net herd growth (loss) rate

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23 When $R_i = 1$, utility become the form $U(x_{idt}) = \ln(x_{idt})$.
[24] In only 77 of 5,704 observations do households lose more than 90% of their herd in a single season.

between sales seasons ($g_{idt}$). In the uninsured case, livestock at the end of each period is calculated by multiplying the herd size during the sales season ($TLU_{idt}$) by the growth rate.[25] Insurance is simulated by adjusting herd size by the net of premiums paid to fully insure and indemnity payments, if received. The sequence of events is as follows: the household enters time period *t* with livestock $TLU_{idt}$, the herd grows by $g_{idt}$ (the rate calculated above) and indemnity payments $In_{idt}$, then is reduced by the amount required to fully insure the updated herd. The premium rate is $Pr_d$ per TLU.[26] The herd size at the end of period *t* is $TLU_{idt+1}$, which is the beginning herd size for period *t+1*.

Indemnity payments in time period *t* are made according to livestock insurance purchased at the end of period *t-1*, the index value from the end of period *t* ($index_{dt}$), and the parameters of the IBLI contract (strike=0.15).[27] To simplify the model, we assume that IBLI contracts last for a single season and that the premium rate for a single season contract is exactly one half the premium rate of an annual IBLI contract. Thus, the household makes a fresh insurance purchase in each period and contracts do not overlap. They model can be described as follows:

(7)
$$U_t\left((TLU_{idt} * g_{idt} + In_{idt}) * (1 - \frac{Pr_d}{1 + Pr_d})\right) = U_t(TLU_{idt+1})$$

$$In_{idt} = TLU_{idt} * \max(index_{dt} - 0.15, 0).$$

This process for simulating the impact of IBLI coverage assumes that premiums are paid through a reduction in herd size and indemnity payments are reinvested directly into livestock. Households in this region have access to livestock markets (Barrett, Bellemare, & Osterloh 2004) and can reinvest indemnity payments into livestock if that is optimal for them. The impacts of this assumption are ambiguous *a priori*.

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[25] The outcome of this calculation is, of course, the original herd size observations.
[26] The household fully insures by solving $TLU'_{idt} - Pr_d\widetilde{TLU}_{idt} = TLU'_{idt} - Pr_d(TLU'_{idt} - Pr_d\widetilde{TLU}_{idt})$, where $TLU'_{idt} = TLU_{idt} * g_{idt} + In_{idt}$ and $\widetilde{TLU}_{idt}$ is the number of livestock insured. The solution is $\widetilde{TLU}_{idt} = TLU'_{idt}/(1 + Pr_d)$ which costs $Pr_d * TLU'_{idt}/(1 + Pr_d)$ in reduced herd size.
[27] We assume that full coverage is purchased on all the livestock owned in each period.

The expected utility with and without insurance is estimated as the average of the utility estimates over all seven periods.[28] We then determine the number of households who have greater expected utility with IBLI coverage than without it at various levels of risk aversion and over the three premium levels. For consistency, we continue to group the index divisions into upper and lower groups.

As expected, fewer households benefit from IBLI as the premium rates increase. At the subsidized rates at which policies were sold during this period, nearly every household is better off with insurance. Perhaps the most interesting case is at the within-sample actuarially fairly price. These findings are driven purely by the intertemporal reallocation of livestock, drawing herds down to pay premiums during good years and receiving indemnity payments in poor years. The reallocation provided by the IBLI schedule improves the expected utility for about 90% of households in the lower division and for a majority in the upper division. The loaded unsubsidized premium rate provides another interesting scenario, those that would benefit if the policies were sold at their commercially sustainable rate. The ratio of households that benefit from IBLI in the upper region is greater with these rates than with the within-sample actuarially fair premiums because the premium continues to fall below the within-sample expected indemnity payment. The loaded premiums are estimated using a much longer dataset than only these eight seasons, which have had an abnormally high number of severe droughts.

The loaded provider rates used here are the same rates as those used in the mean-variance section (Table 3). This utility analysis is able to order all the households and allows for insurance coverage in one period to affect herd size in following periods. With this complete ordering and accounting for dynamic effects due to endogenous herd growth, the proportion of risk averse households that benefit from IBLI increases dramatically from 35% in the mean variance analysis (column 1, Table 3) to more than 55% (Table 4).

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[28] Because growth rate in period *t* includes information from *t+1* we cannot simulate into the final (eighth) period. In addition, we assume that households enter the first period with no insurance coverage.

Note that the relationship between risk aversion and benefits from IBLI is not monotonic, consistent with predictions by Clarke (2011). But in this case, the non-linear relationship between risk aversion and benefits from insuring is only part of the story. For some households, IBLI increases risk but has an expected payoff that is greater than the premium rate even when prices are actuarially fair while for others the opposite is true.[29] The utility function coordinates exchange rates between the moments.

Willingness to pay for seasonal contracts is estimated as the highest premium value at which at least 50% of households are better off with insurance than without it. We also examine how willingness to pay changes across a range of risk preferences. We find that the upper contract region has greater willingness to pay than the lower region (Table 5). Consistent with our findings in Table 4, willingness to pay is always greater than the expected indemnity payment in both regions but the difference is much greater in the lower region. In the lower contract division, at least half of the simulated risk averse households would continue to be better off purchasing IBLI at a rate 42% higher than the expected indemnity rate (3.9%) while in the upper contract division risk averse households have a willingness to pay that is 6.7% above the expected indemnity rate.

This section examined the impact that IBLI coverage has on the net outcomes that household's experience. We find that benefits of IBLI coverage outweigh its cost for a majority of the population and that the majority of households would continue to benefit from IBLI purchases even at much higher premium rates, but those positive net benefits are not universal. The next section examines basis risk at the household level to determine which factors contribute to the net benefits of IBLI.

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[29] Because herd sizes are not constant, households can net profits from always fully insuring even when premiums are equal to the expected index. For example, a household that has a small herd coming into a good season and then a large herd coming into a season that triggers an indemnity payment would net a profit by fully insuring in both seasons even if the premium rate is equal to the two—season average index value.

## Decomposing Basis Risk

Although many, and by some measures most, households benefit from IBLI, there are clear signs that policy holders continue to shoulder significant basis risk. This section examines household-level basis risk to determine which contract and household level characteristics are associated with greater basis risk. In order to focus on shortfalls of the index we make two changes to our procedure. First, outcomes and net outcome are now measured in terms of livestock mortality and net mortality rates rather than survival rates as they often did in the previous section. Survival rates can be recovered by subtracting the outcome from one. Second, we do not include a premium in this analysis so that our estimates are an examination of the relationship between the index and household data rather than the policy premium parameters.

Table 6 summarizes the downside risk without insurance and the downside basis risk associated with index shortfalls during high covariate loss events. Downside risk is estimated using the semi-variance method described in Section 4. Downside basis risk is estimated as the semi-variance of the difference between livestock mortality rates and the indemnity rate, conditional on high livestock mortality rates (>0.15) and a shortfall in indemnity rates. This focuses our analysis on those periods when households suffer severe losses and on IBLI's performance in reducing risk caused by such losses.

The overall average reduction to squared deviations from the strike during high loss events due to IBLI coverage is about 19%. This section examines the heterogeneity in the remaining (basis) risk in order to understand what factors determine the net benefits or losses generated by insuring with IBLI. We begin by examining design risk as an indicator of index accuracy. We find that the IBLI index successfully accounts for about 59% of covariate risk in the four divisions. We then examine the association of idiosyncratic risk with household characteristics, scale of covariate region, and local conditions. We find average idiosyncratic losses and variance in those losses are positively associated with greater dependency ratios and income diversification away from livestock. Perhaps most striking is how little idiosyncratic risk can be explained by household characteristics or local fixed effects. A large share of losses in this region appear truly random.

***Design Risk***

Design risk arises due to differences between the index and the covariate losses. The level of design risk is necessarily shared among all policy holders in the same index division (administrative districts in this case). Figure 2 shows a map of the Marsabit region and the five index divisions; a different index value is calculated for each.

Figure 6 plots the 32 index-covariate loss observations on the domain described by Figure 1. Fitted lines above and below the strike are also included, along with confidence intervals. These regressions are estimated according to Equation (5) by restricting the division-level intercepts and slope coefficients to be equal across divisions ($\alpha_d = \alpha, \delta_d = \delta \; \forall \; d$). There is clearly large variation across the sample in how well the index performs. Below the strike, the fitted line lies above the 45 degree line indicating that index is likely to underestimate division level mortality rates when those rates are below 0.15. Above the strike, the index generally overestimates the covariate losses. In total, there are eight (25%) observed false positives and four (12.5%) false negatives. The high rate of discrete error observed on an index designed explicitly to minimize basis risk and tested out-of-sample using a data set other than the design data (Chantarat et al. 2013) serves as a strong caution against overconfidence in the quality of index insurance products.

To examine the accuracy of the index we focus on those events when covariate losses were greater than the strike (above the horizontal red line in Figure 6). Table 7 provides summary statistics of the covariate and design risk associated with those events. The covariate risk is estimated using the target semi-variance in order to examine the risk associated with severe events and represents an average of only 27.2% of the total downside risk estimated in Table 6. Design risk is then calculated as the semi-variance of the shortfall of the index during those events. Notice that the average conditional design risk represents 9.6% of the average conditional basis risk presented in Table 6, foreshadowing the large role that idiosyncratic risk plays. The precision is an estimate of the portion of conditional covariate risk that the index covered. On average, the index reduces covariate risk by about 59% but there is significant heterogeneity in covariate risk and index precision between divisions.

Estimating Equation (3) by regressing covariate losses on the index shows that there are systematic differences between the index and covariate losses (Table 8). The index consistently underpredicts both covariate losses and conditional covariate losses; the estimated index coefficient is significantly less than one in both the restricted and unrestricted case. The $R^2$ statistics provide an indication of the amount of covariate risk that the index is able to account for. Once again, the index performs much better when the sample is restricted to high loss events.

The index under-predicts losses as is evident by the much greater number of points above the strike but to the left of the 45 degree line in Figure 6. This structural relationship between the index and covariate losses means that a rotation of the index according to the parameter estimates in Table 8 could increase the accuracy of the insurance product during these severe covariate events within this sample period.

A second potential approach to reducing design risk is to adjust the strike. Calculating design error conditional on covariate losses greater than the strike where the strike falls in the interval $[0,0.25]$, we examine how well the index predicts covariate losses above the strike at various strike levels. We find that varying the strike rate has no significant impact on the accuracy of the index; there is a great deal of variation in design error at all strike levels (Figure 7).

Design errors are a significant component of basis risk. These design errors arise due to covariate losses that could be indemnified by the IBLI policy but are not captured by the index as presently designed even though it was explicitly designed to minimize basis risk. Our estimates of the relationship between the index and covariate losses point towards a systematic error that could be addressed by rotating the index to increase predicted livestock mortality rate. The strike level is a second parameter that could be readily and easily changed if there were gains in precision to be had. But there is no evidence to support one strike level over another. Because the expected absolute value of design error does not change significantly as strike levels change, they might be left open as a contract parameter chosen according to consumer or provider preferences.

***Idiosyncratic Risk***

A second and far larger portion of basis risk (about 64%, on average) arises due to idiosyncratic losses, or mortality not reflected in the division average. Although much idiosyncratic loss is likely associated with random events, it may also have a systematic relationship with household or geographic characteristics. If such patterns are known to prospective purchasers, a form of adverse selection subtly returns even though index insurance is pitched in part as an approach to obviate adverse selection problems in conventional insurance.[30] In this section we examine factors that contribute to idiosyncratic risk.

The size of the covariate region may affect the level of covariate (and thus remaining idiosyncratic) risk. In theory, index products capture a greater portion of risk as the size of the index region shrinks. The entire IBLI study region covers about 66,700 km$^2$ (about the size of West Virginia) and is composed of four divisions. Each division consists of sublocations (administrative subunits within divisions), 16 of which are captured by the survey.

Figure 8 shows the ratio of covariate risk to average total risk at various covariate scales.[31] This ratio

[30] Note that this sort of adverse selection does not affect equilibrium pricing of the insurance since it does not affect insurer indemnification rates. It merely induces selection effects among prospective clients.

[31] The numerator, covariate risk, is the variance of covariate losses within each covariate region ($CR_d = Var_t[\frac{1}{N_d}\sum_i L_{idt}]$). The denominator is the within region average household variance in losses or average risk ($\overline{Risk}_d = \frac{1}{N_d}\sum_i Var_t[L_{idt}]$).

captures the potential risk faced by households that could be covered by an index product at each covariate scale in this setting. The average ratio of covariate to total risk more than doubles as the covariate area shrinks from a large aggregate region composed of a single IBLI division, to separate divisions defined by sublocation. There is also a great deal of variance between sublocations. Covariate risk within sublocations is less than 15% of total risk in five survey sublocations, while it is greater than 40% in four. In those locations with very low covariate risk, even a local and extremely accurate index product could not cover much of the risk that households face. On the other hand, households in many survey sublocations face a great deal of covariate risk, making them prime candidates for index insurance.[32]

At the division level, there is clearly the potential for geographically defined patterns to the benefits of IBLI. Risk averse households in sublocations most similar to their division averages are likely to benefit more from insurance covering covariate losses than would households in sublocations with little covariate risk. In addition, three of the index divisions were, until recently, aggregated into a single contract division (the Low IBLI contract includes sublocations Dakabaricha through South Horr from left to right on the x-axis of Figure 8) with a single premium rate, but maintain separate indices. If the division level index correctly predicts covariate losses within each of the three divisions, the Central/Gadamoji division (sublocations Dakabaricha, Dirib Gombo, Sagante, and Karare) will have much higher expected indemnity payments then the remaining households in the contract region even though they pay the same premium rate. In that case, policy holders in the other two divisions are inadvertently subsidizing the premium rate in the Central/Gadamoji division and we should expect spatially defined opportunistic behavior (i.e., spatial adverse selection) to emerge.

There is also a great degree of variation between households—and even within households—over time. In

[32] It is reasonable to expect that the differences in average ratio of covariate risk to risk is related to variation in the shapes and sizes of the sublocations. Regressing the sublocation average ratio of covariate risk to risk on sublocation area and the ratio of area to perimeter yields no statistical evidence of such a relationship. Analysis not included.

this final analysis of basis risk patterns, we explore which factors are associated with deviations of households from the average losses experienced within their index division. A number of easily observed characteristics could reasonably impact livestock loss rates. For example, Lybbert et al. (2004), studying a very similar system in neighboring southern Ethiopia, find a strong positive association between herd size and livestock mortality rate, which would translate into a similar relationship with respect to idiosyncratic losses. Access to labor, herd size and composition, cash liquidity, informal insurance network participation and level of risk aversion all might impact how well a household's herd fares compared to the household's division's average losses. A description of the household characteristics considered here and their summary statistics are found in Appendix C. Idiosyncratic losses and the semi-variance of idiosyncratic losses are regressed on household characteristics in order to determine which are associated with idiosyncratic risk. The semi-variance is used rather than variance in order to isolate variance associated with household losses that are greater than covariate losses.

Spatial correlation of idiosyncratic risk could be an effect of local environmental shocks or spatially correlated household characteristics. Although we cannot fully disentangle the two here, we can examine household characteristics for explanatory value with and without sublocation fixed effects, in order to reveal when factors are important due to between-sublocation variation and within-sublocation variation. Sublocation fixed effects alone are able to account for a fairly large portion of variation in downside risk (idiosyncratic semi-variance) between households ($R^2$=0.136, column 4, Table 9) but very little of the variation in idiosyncratic losses ($R^2$=0.031, column 1, Table 9). Indeed, household characteristics do no better in explaining idiosyncratic losses or risk than do sub-location fixed effects as revealed by comparing columns 1 and 2, and 4 and 5 in Table 9. Yet adding controls for sublocation fixed effects has little impact of the estimated relationships between household characteristics and idiosyncratic risk components (column 2 vs. 3, column 5 vs. 6).

The ratio of income generated from livestock is the only livestock-related characteristic that is consistently (negatively) associated with idiosyncratic risk, even when we control for sublocation average idiosyncratic risk. There does seem to be a weak relationship between herd size and exposure to idiosyncratic risk, but those effects are not consistent and the average marginal effect of herd size is statistically indistinguishable from zero except for the model in column (2), Table 9 (analysis not included). Households with relatively more dependents also have greater idiosyncratic risk.

What is perhaps the most striking finding of this analysis is how little idiosyncratic risk is associated with household characteristics or can be captured by sublocation fixed effects. Idiosyncratic losses cannot be very well explained by sublocation average losses nor by a host of household characteristics that could reasonably be associated with livestock mortality rates. For example, herd size and composition is for the most part unrelated to idiosyncratic risk. Idiosyncratic losses seem to be almost entirely random while variance in losses is much more predictable, but still more than 70 percent of the variation in semi-variance is unexplained by readily observable household characteristics and sub-location fixed effects, as might be practical for targeting purposes.

As a robustness check, we estimate a fixed effects model to determine if unobserved time-invariant household characteristics drive our findings. Only column (2) from Table 9 can be estimated in this way because the within-household variation in sublocation is nearly zero and semi-variance of idiosyncratic losses has no within household variance. In addition, risk aversion, age, and gender variables are dropped due to lack of within household variation. The fixed effects model reported in Appendix D also captures very little of the rate of idiosyncratic losses and there is little indication that those losses are anything but random.

In addition, we test to make sure that our approach and findings in this section are compatible with the benefits found in section 4. To do so, we re-estimate columns (4)-(6) in Table 9 replacing the dependent variable with a measurement of net benefits. As expected, variation in design risk between divisions results in a high degree of correlation between benefits and division ($R^2$=0.289) while the randomness in idiosyncratic risk allows household characteristics alone to explain very little of the between-household variation in benefits from IBLI ($R^2$=0.183). See appendix E for analysis.

In summary, households that depend on livestock for only a small amount of their income but have relatively large herds and have many dependents will likely suffer from high idiosyncratic losses even after accounting for community fixed effects. The sublocation effects seem to be mostly in addition to household characteristics indicating that they capture factors associated with local environmental conditions. But none of these observable variables explain much idiosyncratic loss, which is both large in magnitude and mainly random.

## Discussion

Index insurance provides a promising means for overcoming many of the barriers that have prevented access to insurance in poor rural regions of the world. But index insurance has its own weaknesses and is only appropriate in certain risk environments and at certain scales. Knowing both the idiosyncratic and design components of basis risk is an important factor in determining the value proposition of index insurance. Regrettably, in practice neither the consumer nor the provider has perfect information. Providers can only learn about the relative magnitude of covariate risk and the accuracy of their index by collecting longitudinal consumer-level information to determine covariate risk, a rare practice. In a similar fashion, consumers can only begin to estimate the design risk once they have observed a number of periods of product coverage.

The result is that although basis risk is widely recognized as the Achilles heel of index insurance, it has to date gone unmeasured and unstudied in index insurance products developed for smallholder farmers and herders in the low-income world. This study provides the first detailed study of basis risk related to index insurance products in developing countries. It examines an insurance contract that is best-in-class in at least two important ways. First, there is a great deal of evidence that large covariate droughts are the largest cause of livestock mortality in the population for whom IBLI is available (e.g., Barrett et al. 2006; Lybbert et al. 2004; McPeak, Little, & Doss 2012). Second, IBLI polices are based on an index that was generated using a long panel of household data and regression expressly to minimize basis risk (Chantarat et al. 2013). Other index products fielded in the developing world typically lack similar foundations. These features have earned IBLI numerous international awards for innovation and should make this product something close to a best case scenario for assessing basis risk in index insurance products for farmers and herders in the developing world.

The results are only mildly encouraging and offer a cautionary tale about the prospective benefits of index insurance. Tests for stochastic dominance underscore that index insurance with a positive probability of large false negatives cannot stochastically dominate no insurance. Mean-variance and utility analysis show that IBLI coverage likely improves the outcomes faced by most – but far from all –households, but only modestly. Most importantly, fully insuring with IBLI leaves households bearing a significant amount of uninsured risk. Some of this basis risk is due to design risk as the index is an imperfect predictor of covariate livestock mortality rates, underscoring the need for careful *ex post* evaluation and adjustment of index products even when designed *ex ante* to minimize basis risk.

A second, much larger, portion of basis risk is due to idiosyncratic risk. Although the study population is plagued by severe droughts during which nearly all households experience higher than normal livestock mortality, households also experience a tremendous degree of nearly random idiosyncratic variation in every season, even in high covariate loss seasons. These findings echo earlier research showing a dramatic increase in the variation of herders' expectations of their own herd's dynamics when those herders expect poor rainfall conditions rather than good or normal conditions (Santos & Barrett 2006). In addition, the degree of covariate risk is closely tied to how covariate losses are defined spatially and temporally. The ratio of covariate risk to total risk varies by more than a factor of 9 across the 16 sublocations included in this study.

This research illustrates the complexity of providing index insurance, even in an environment that in some respects seems ideal. It emphasizes the spatial sensitivity of covariate risk to the covariate region and the resulting prospect for adverse selection. It reveals that basis risk and especially idiosyncratic risk are substantial, pointing towards the continued importance of informal risk sharing agreements even when index insurance is available. An optimally designed index insurance product yields risk-reducing welfare gains for many prospective purchasers but offers far-from-full coverage. Caution seems warranted in the promotion of index insurance as a risk management instrument for low-income populations underserved by conventional insurance markets.

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## Figures

**Figure 1.** The domain of basis error

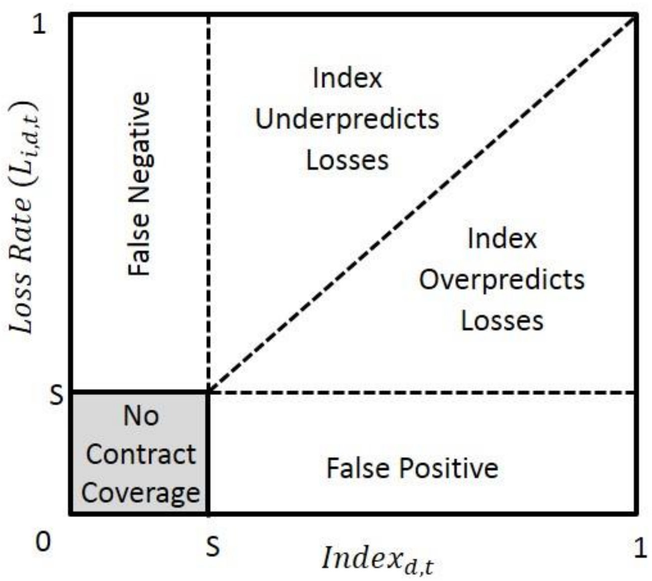



**Figure 2.** IBLI Geographical Coverage and Index Divisions

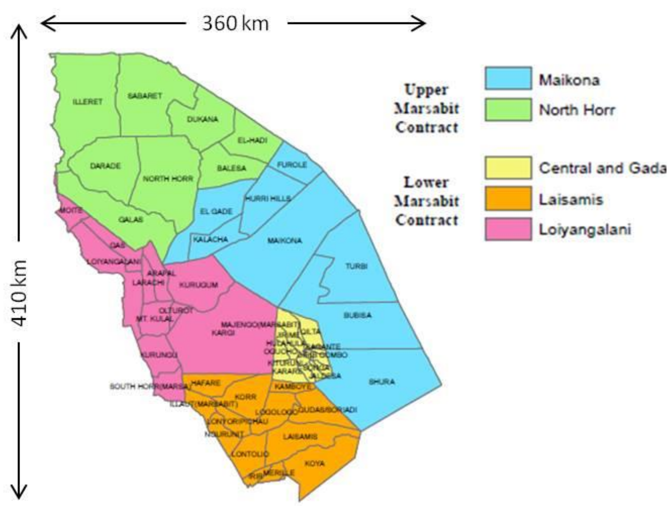
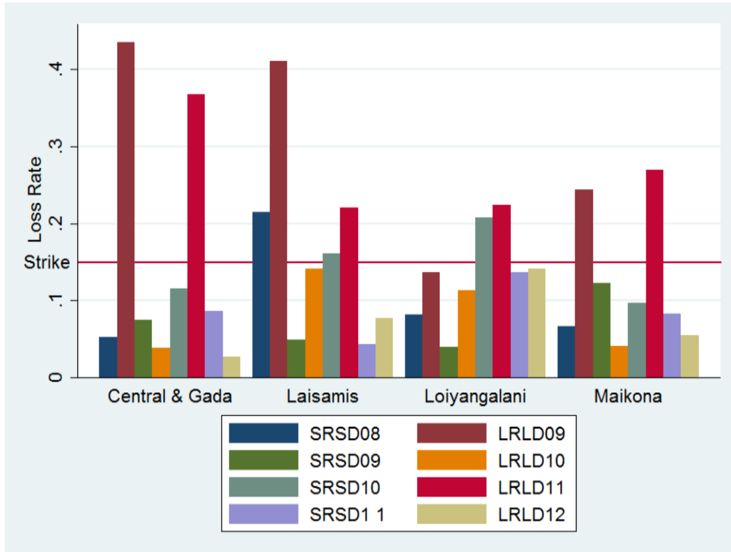
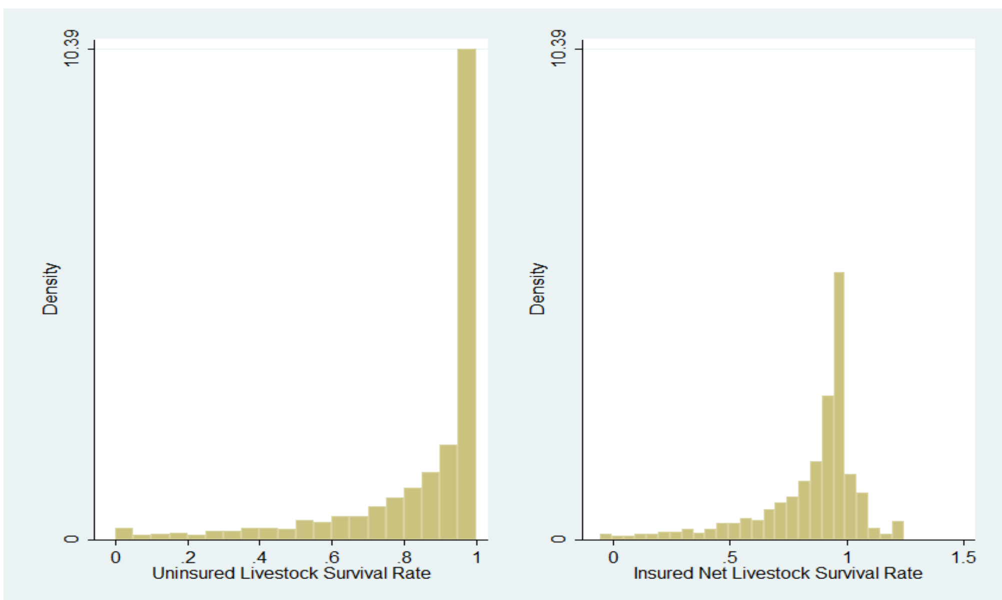


**Figure 3.** Division level average livestock mortality rate across seasons




**Notes:** The index strike value is 0.15. SRSD is short rain/short dry insurance season. LRLD is the long rain/long dry insurance season.

**Figure 4.** Histograms of livestock survival rate and net livestock survival rate with full insurance




**Note:** Insured net livestock survival rate is equal to seasonal survival rate less the loaded unsubsidized premium plus indemnity payments.

**Figure 5.** Cumulative distribution of livestock survival rate and net outcome:

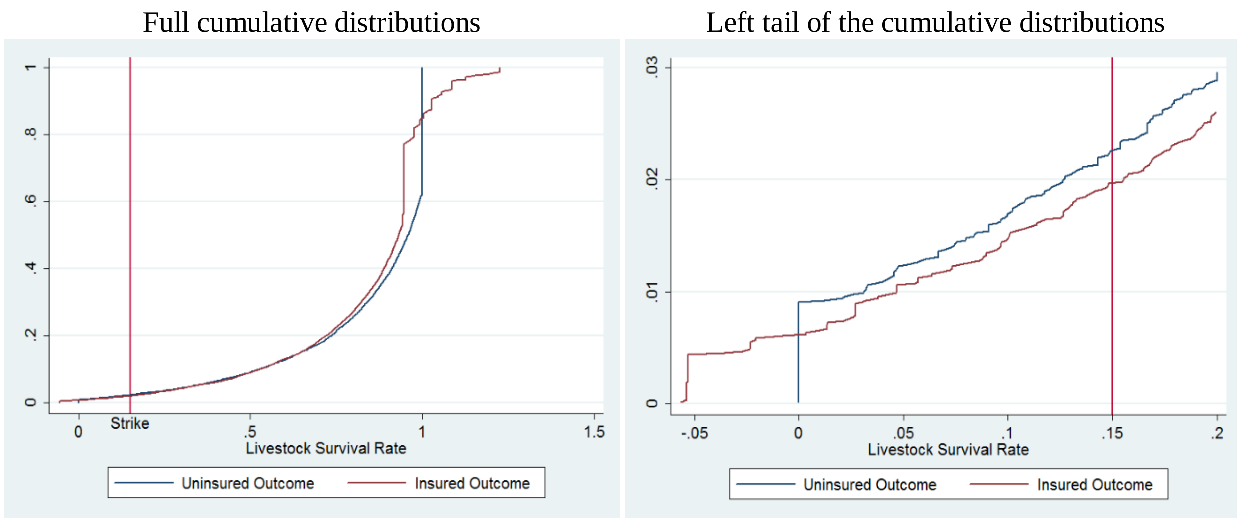
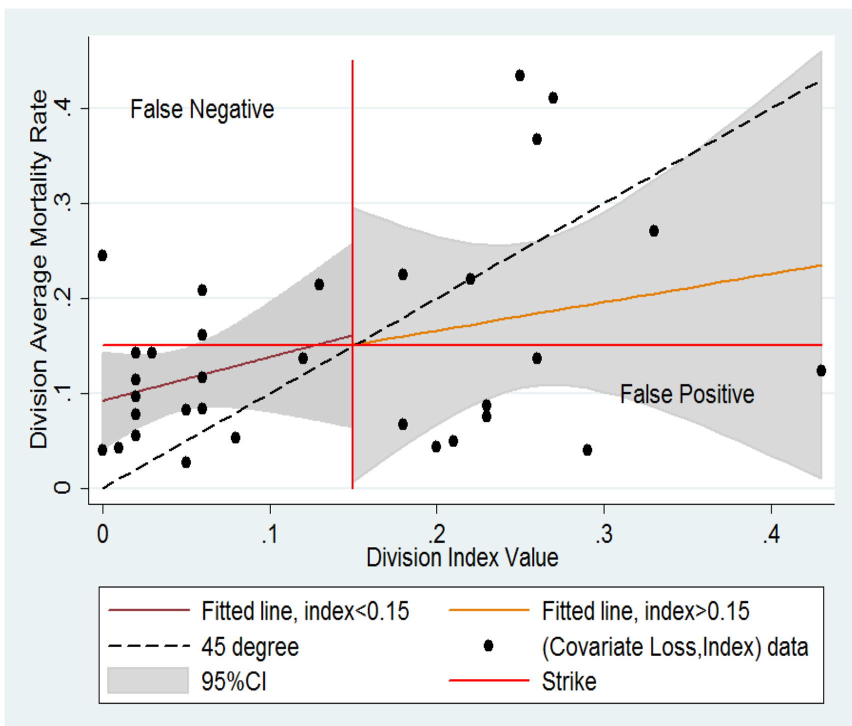



**Figure 6**. Design error above and below the strike (0.15)




**Notes:** Covariate loss-index observations are seasonal division average mortality paired with the index value for that division-season. Fitted lines and confidence intervals are generated by regressing livestock mortality rates on the index.

**Figure 7**. Index accuracy at various covariate loss strike levels

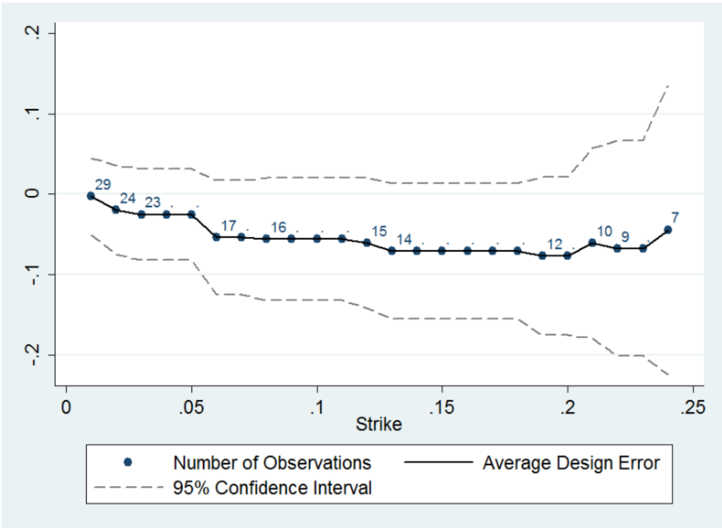
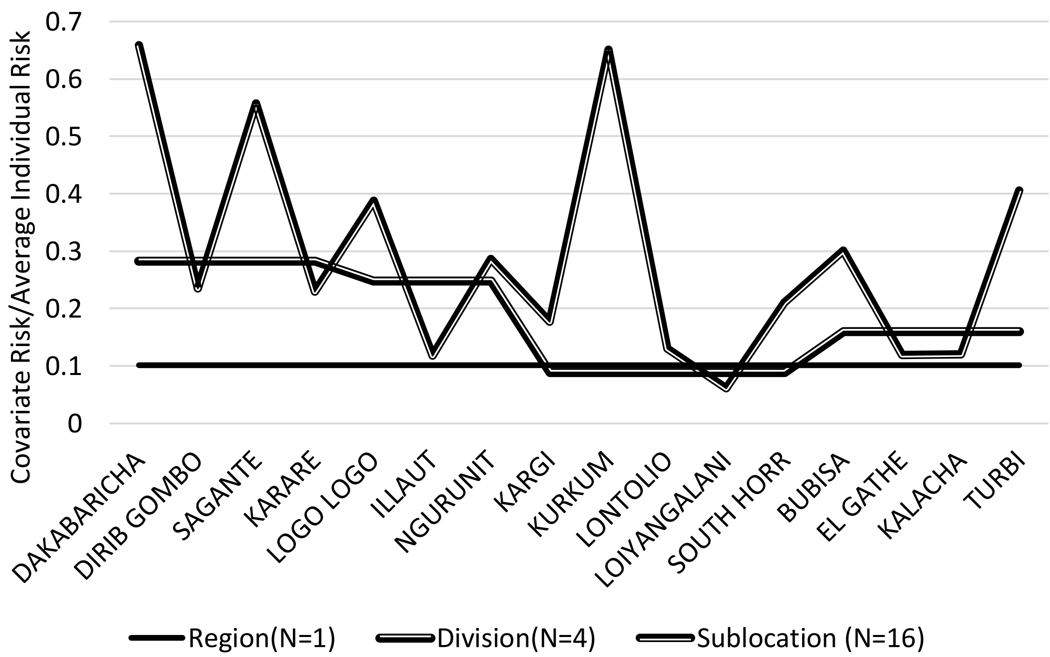



**Figure 8.** Ratio of average covariate risk to average individual risk at different geographic scales




| | Average Risk (R) | Average Covariate Risk (CR) | | |
|---|---|---|---|---|
| | | Entire Sample | Division | Sub-Location |
| Variance | 0.0457 | 0.0046 | 0.0081 | 0.0119 |
| Ratio (CR/R) | 1 | 0.101 | 0.155 | 0.223 |

## Tables

**Table 1.** The impact of IBLI on average within-household mean, variance, and skewness of survival rate

| Statistic | Uninsured | Insured | Difference | Standard Error | t-statistic |
|---|---|---|---|---|---|
| Mean | 0.860 | 0.847 | 0.012 | 0.001 | 21.47 |
| Variance | 0.046 | 0.048 | -0.002 | 0.001 | -2.88 |
| Skewness | -1.17 | -0.65 | -0.520 | 0.076 | -6.87 |

**Table 2.** Impact of IBLI on downside risk in mortality rate during severe events (mortality rate > 0.15)

| Premium | Statistic | Uninsured | Insured | Difference | t-statistic |
|---|---|---|---|---|---|
| **Commercial**[1] | Expected Losses >.15 | 0.084 | 0.087 | -0.003 | -3.63*** |
| | Semi-Variance | 0.038 | 0.040 | -0.001 | -2.22** |
| **Actuarially Fair**[2] | Expected Losses >.15 | 0.084 | 0.083 | 0.001 | 1.22 |
| | Semi-Variance | 0.038 | 0.038 | 0.001 | 1.43 |
| **Subsidized**[3] | Expected Losses >.15 | 0.084 | 0.076 | 0.008 | 9.79*** |
| | Semi-Variance | 0.038 | 0.034 | 0.004 | 7.50*** |

[1]The commercial annual premium rates are Central/Gadamoji=10.6%, Laisamis=11.3%, Loiyangalani=9.2%, and Maikona=10.7%. [2]The within-sample actuarially fair annual premium rates are Central/Gadamoji=9.25%, Laisamis=7.5%, Loiyangalani=7.0%, and Maikona=12.25%. [3]At that time that this data was collected, the subsidized annual rates were Central/Gadamoji=3.325%, Laisamis=3.325%, Loiyangalani=3.325%, and Maikona= 5.5%.

**Table 3.** Proportion of households for whom IBLI improves their position with respect to each statistic

| Statistic | Proportion | |
|---|---|---|
| | **Loaded & Unsubsidized** | **Subsidized** |
| Mean | 0.304 | 1.000 |
| Variance | 0.346 | 0.346 |
| Skewness | 0.818 | 0.818 |
| Semi-Variance | 0.354 | 0.595 |

**Table 4.** Proportion of households that are better off with IBLI than without

| Coefficient of Risk Aversion | Subsidized Rate[1] Lower | Subsidized Rate[1] Upper | Actuarially Fair[2] Lower | Actuarially Fair[2] Upper | Loaded & Unsubsidized[3] Lower | Loaded & Unsubsidized[3] Upper |
|---|---|---|---|---|---|---|
| R=0 *(risk neutral)* | 0.999 | 0.938 | 0.942 | 0.536 | 0.626 | 0.741 |
| R=1 | 0.975 | 0.914 | 0.921 | 0.584 | 0.613 | 0.737 |
| R=2 *(risk averse)* | 0.966 | 0.912 | 0.890 | 0.605 | 0.569 | 0.748 |

[1]At that time that this data was collected, the annual subsidized rates were Central/Gadamoji=3.325%, Laisamis=3.325%, Loiyangalani=3.325%, and Maikona= 5.5%. [2]The within-sample actuarially fair annual premium rates are Central/Gadamoji=9.25%, Laisamis=7.5%, Loiyangalani=7.0%, and Maikona=12.25%. [3]The commercial annual premium rates are Central/Gadamoji=10.6%, Laisamis=11.3%, Loiyangalani=9.2%, and Maikona=10.7%.

**Table 5**. Average willingness to pay for seasonal coverage as a share of insured livestock value

| Coefficient of Risk Aversion | Mean willingness to pay Lower | Mean willingness to pay Upper |
|---|---|---|
| R=0 *(risk neutral)* | 5.52% | 6.28% |
| R=1 | 5.54% | 6.52% |
| R=2 *(risk averse)* | 5.84% | 6.86% |

**Table 6.** Risk without insurance and basis risk with insurance due to periods with high covariate livestock mortality rates

| | Central/Gadamoji | Laisamis | Loiyangalani | Maikona | Overall |
|---|---|---|---|---|---|
| Conditional Risk [1] | 6.57 | 4.44 | 3.08 | 3.09 | 3.83 |
| Conditional Basis Risk [1] | 4.82 | 3.40 | 2.87 | 2.10 | 3.12 |
| Observations | 159 | 109 | 250 | 226 | 744 |

[1] Conditional (downside) risk is estimated using semi-variance which is calculated by $100 * \frac{1}{T-1}\sum_{t=1}^{T}(O_{idt} - \dot{O}_{dt})^2 I(Z_{idt}))$ where $O_{dt}$ is the outcome experienced in division d, in time period $t$, $\dot{O}_{dt}$ is the target, and $I(Z_{idt})$ is an indicator function that is equal to one if $O_{idt} > \dot{O}_t$ and equal to zero otherwise. Conditional risk is calculated using $O_{idt} = L_{i,d,t}$ and $\dot{O}_{dt} = 0.15$. Conditional basis risk is calculated using $O_{idt} = \max(L_{i,d,t} - 0.15, 0)$, $\dot{O}_t = \max(index_{dt} - 0.15, 0)$ to measure risk associated with shortfall in the index during high losses events.

**Table 7.** Mean covariate risk and design risk during seasons when covariate losses were above the strike

| | **Central/Gadamoji** | **Laisamis** | **Loiyangalani** | **Maikona** | **Overall** |
|---|---|---|---|---|---|
| Conditional Covariate Losses (rate)[1] | 0.400 | 0.251 | 0.216 | 0.257 | 0.275 |
| Conditional Index (rate)[1] | 0.255 | 0.170 | 0.120 | 0.165 | 0.176 |
| | | | | | |
| Conditional Covariate Risk (X100)[2] | 1.848 | 1.095 | 0.126 | 0.328 | 0.849 |
| Conditional Design Risk (X100)[2] | 0.661 | 0.340 | 0.075 | 0.120 | 0.299 |
| Precision[3] | 0.64 | 0.69 | 0.40 | 0.63 | 0.59 |
| | | | | | |
| Seasons w/ mean loss>0.15 | 2 | 4 | 2 | 2 | 10 |

[1] Division averages for seasons during which the covariate losses are greater than 0.15. [2]Conditonal (downside) risk is estimated using semi-variance which is calculated by $100 * \frac{1}{T-1}\sum_{t=1}^{T}(O_{dt} - \dot{O}_{dt})^2 I(O_{dt}))$ where $O_{dt}$ is the outcome experienced in division d, in time period $t$, $\dot{O}_{dt}$ is the target, and $I(O_{dt})$ is an indicator function that is equal to one if $O_{dt} > \dot{O}_t$ and equal to zero otherwise. Conditional covariate risk is calculated using $O_{dt}$ = covaritate losses $(CL_{dt})$ and $\dot{O}_t = 0.15$. Conditional design risk is calculated using $O_{dt} = \max(CL_{dt} - 0.15{,}0)$ and $\dot{O}_t = \max(index - 0.15{,}0)$. [3] Precision is the ratio of conditional covariate risk captured by the index.

**Table 8**. The relationship between covariate losses and the index

| | Covariate losses | Conditional covariate losses[1] |
|---|---|---|
| Index | 0.335** | 0.547* |
| | (0.160) | (0.243) |
| Constant | 0.096** | 0.179*** |
| | (0.029) | (0.050) |
| | | |
| F-stat: $H_0$: $\alpha_d = 0$ $and$ $\delta_d = 1$ | 8.67*** | 9.55*** |
| F-stat: $H_0$: $\delta_d = 1$ | 17.24*** | 3.49* |
| | | |
| Observations | 32 | 10 |
| R-squared | 0.127 | 0.389 |

[1] Conditional covariate losses are covariate losses during season's when covariate losses were greater than the strike (0.15). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 9.** Factors that contribute to idiosyncratic livestock mortality rate and downside risk

| | Idiosyncratic Loss Rate (IL) | | | Semi-Variance(IL)* | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| Age (/100) | | -0.1400 | -0.1800 | | -0.0445 | -0.0788 |
| | | (0.1708) | (0.1499) | | (0.0947) | (0.0880) |
| $Age^2$ ($age^2/100^2$) | | 0.1028 | 0.1578 | | 0.0165 | 0.0537 |
| | | (0.1423) | (0.1282) | | (0.0823) | (0.0796) |
| Gender (=1 if male) | | -0.0200* | -0.0058 | | -0.0078 | -0.0057 |
| | | (0.0114) | (0.0111) | | (0.0052) | (0.0050) |
| Household size (count/100) | | -0.1204 | -0.1342 | | -0.0622 | -0.0512 |
| | | (0.2660) | (0.2455) | | (0.1394) | (0.1258) |
| Dependency ratio | | 0.0824** | 0.0588* | | 0.0599*** | 0.0471*** |
| | | (0.0346) | (0.0332) | | (0.0180) | (0.0176) |
| Asset index# | | -0.0387 | -0.0481 | | 0.0216 | 0.0412 |
| | | (0.0936) | (0.1324) | | (0.0640) | (0.0814) |
| Asset index squared# | | 0.0866 | 0.1973 | | -0.1458 | -0.1851 |
| | | (0.4089) | (0.4730) | | (0.2610) | (0.2872) |
| HSNP participant | | 0.0034 | -0.0139 | | -0.0046 | -0.0094 |
| | | (0.0120) | (0.0123) | | (0.0058) | (0.0066) |
| Ratio herd camels& | | 0.0031 | 0.0155 | | 0.0040 | 0.0242 |
| | | (0.0310) | (0.0326) | | (0.0221) | (0.0250) |
| Ratio herd cattle& | | -0.0055 | 0.0040 | | 0.0119 | 0.0228 |
| | | (0.0223) | (0.0209) | | (0.0252) | (0.0319) |
| Herd size (TLU/100)& | | 0.0320 | -0.1572 | | -0.0505 | -0.1889** |
| | | (0.0857) | (0.1043) | | (0.0732) | (0.0845) |
| Herd $size^2$ ($TLU^2/100^2$)& | | -0.0265 | 0.1433 | | 0.1542 | 0.3725** |
| | | (0.1170) | (0.1372) | | (0.1379) | (0.1490) |
| Herd $size^3$ ($TLU^3/100^3$)& | | -0.0049 | -0.0473 | | -0.0751 | -0.1709** |
| | | (0.0357) | (0.0428) | | (0.0655) | (0.0683) |
| Ratio income from livestock# | | -0.0253 | -0.0245 | | -0.0399*** | -0.0329 |
| | | (0.0154) | (0.0184) | | (0.0129) | (0.0202) |
| Log (1+Savings)# | | 0.0020 | 0.00242 | | -0.0019* | -0.0015 |
| | | (0.0019) | (0.0023) | | (0.0010) | (0.0014) |
| Social groups (count)# | | -0.0100 | -0.0083 | | -0.0074 | -0.0062 |
| | | (0.0097) | (0.0106) | | (0.0048) | (0.0052) |
| Moderately risk averse | | -0.0144 | -0.0127 | | -0.0017 | 0.0002 |
| | | (0.0112) | (0.0085) | | (0.0063) | (0.0046) |
| Extremely risk averse | | -0.0048 | -0.0086 | | 0.00194 | -0.0007 |
| | | (0.0127) | (0.0096) | | (0.0064) | (0.0050) |
| Sublocation Fixed Effects (16) | Yes | No | Yes | Yes | No | Yes |
| F-stat testing: All sublocation Fixed Effects=0 | 6.06*** | | 3.54*** | 3.84*** | | 3.59*** |
| Observations | 5,880 | 5,113 | 5,113 | 735 | 735 | 735 |
| R-squared | 0.031 | 0.019 | 0.041 | 0.136 | 0.153 | 0.247 |

Regression also included an intercept term. * Semi-variance of idiosyncratic losses is calculated as the within household sum of squares of $\widetilde{IL_{i,t}}$ where $\widetilde{IL_{i,t}} = \max(IL_{i,t}, 0)$ #Variable is lagged by one period in the idiosyncratic losses estimation in order to reduce potential endogeneity. &Variable uses seasonal average monthly herd size. Household clustered-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

# Appendices

### *Appendix A: Attrition and Selection Analysis*

The level of sample attrition is less than 4% per year; 37 households between first and second rounds, 30 between second and third rounds, and 25 between third and fourth rounds. There are significant differences between the survey households that exit and those that remain in the survey (Table A1). Households that leave the survey are larger, consume less per person, and generate a greater portion of income from livestock related activities. About 12% of the remaining households are dropped because they have periods with zero reported livestock so that their livestock mortality rate is undefined. The dropped households are similar to the exit households but also have significantly lower education, greater herd size and income than the control households.

**Table A1.** Balancing Table (2009 data): Attrition, dropped, and full data households (2009-2012)

| Variable | Control[1] (N=736) | Exit, or Dropped | Difference | T-statistic | |
|---|---|---|---|---|---|
| *Exit households (N=92[2])* | | | | | |
| Max education[3] | 4.31 | 4.74 | -0.43 | -0.88 | |
| Household members (count) | 5.76 | 4.89 | 0.87 | 3.38 | *** |
| Dependency ratio[4] | 0.62 | 0.59 | 0.02 | 1.03 | |
| Consumption per capita (KSH) | 1,433 | 1,807 | -374 | -2.76 | *** |
| TLU owned[5] | 19.71 | 16.14 | 3.57 | 1.28 | |
| Income (KSH) | 5,259 | 3,504 | 1,755 | 1.01 | |
| Ratio of income form livestock | 0.56 | 0.30 | 0.26 | 3.54 | *** |
| Risk category[6] | 2.49 | 2.65 | -0.16 | -0.84 | |
| Savings (KSH) | 6,893 | 13,795 | -6,901 | -0.98 | |
| *Households with zero livestock holdings in at least one period (N=96)* | | | | | |
| Max education[3] | 4.31 | 5.28 | -0.98 | -2.03 | ** |
| Household members (Count) | 5.76 | 4.79 | 0.97 | 3.87 | *** |
| Dependency Ratio[4] | 0.62 | 0.62 | 0.00 | -0.21 | |
| Consumption per capita (KSH) | 1,433 | 2,070 | -637 | -4.68 | *** |
| TLU owned[5] | 19.71 | 4.30 | 15.41 | 5.78 | *** |
| Income (KSH) | 5,259 | 5,258 | 1.34 | 0.00 | |
| Ratio of income form livestock | 0.56 | 0.08 | 0.48 | 9.33 | *** |
| Risk category[6] | 2.49 | 2.73 | -0.23 | -1.28 | |
| Savings (KSH) | 6,893 | 5,217 | 1,676 | 0.26 | |

[1] Households that are in all four survey rounds and never have zero livestock for an entire IBLI season (March-September or October-February). [2] N=92 is composed of 88 households that left the survey and were replaced, and 4 that miss one survey round but did not leave the survey. [3] Maximum level of education achieved by any household member where 1-8 are standards, 9-12 are forms 1-4, 15 is a diploma, 16 a degree and 17 a postgraduate degree. [4] Ratio of household members aged less that 15 or older than 54 years to the total household size. [5] Tropical Livestock Units (TLU) are calculated as follows: Camel=1TLU, Cattle=0.7 TLU, Sheep & goats=0.1 TLU. [6] Risk categories are discrete values ranging from 0 (most risk averse) to 5 (most risk taking) elicited using a real lottery with variation in expected winnings and variance of outcomes similar to that described by Binswanger (1980). Level of statistical significance indicated by *** (p<0.01), ** (p<0.05) and * (p<0.1).

*Appendix B: Index Values and Theoretical Indemnity levels*

This research includes analysis of basis risk before IBLI was available for sale. In those non-sale periods, there are no publically available index values. In the seasons before LRLD 2010, index values were collected from internal documents: "IBLI Pricing 2010" (SRSD 2008 LRLD 2009 and SRSD 2009) and "IBLI Marsabit Pricing June 2012" (LRLD 2010). The remainder (SRSD 2010 though LRLD 2012) were collected from the publically available IBLI index archive available at http://livestockinsurance.wordpress.com/ibli-kenya/mortality-index-update/index-archive//.

The indemnity payments represent a percentage of the value of the insured asset and are calculated according to the IBLI contracts (max (index-0.15,0)).

**Table B1.** IBLI index values and imputed indemnity payments

| | Central & Gadamoji | | Laisamis | | Loiyangalani | | Maikona | |
|---|---|---|---|---|---|---|---|---|
| Seasons | Index | Indemnity | Index | Indemnity | Index | Indemnity | Index | Indemnity |
| SRSD 2008[1] | 0.08 | 0.00 | 0.13 | 0.00 | 0.05 | 0.00 | 0.18 | 0.03 |
| LRLD 2009[1] | 0.25 | 0.10 | 0.27 | 0.13 | 0.26 | 0.11 | 0.00 | 0.00 |
| SRSD 2009[1] | 0.23 | 0.08 | 0.21 | 0.06 | 0.29 | 0.14 | 0.42 | 0.27 |
| LRLD 2010 | 0.00 | 0.00 | 0.02 | 0.00 | 0.02 | 0.00 | 0.01 | 0.00 |
| SRSD 2010[1] | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.02 | 0.00 |
| LRLD 2011 | 0.26 | 0.11 | 0.22 | 0.07 | 0.18 | 0.03 | 0.33 | 0.18 |
| SRSD 2011 | 0.23 | 0.08 | 0.20 | 0.05 | 0.12 | 0.00 | 0.06 | 0.00 |
| LRLD 2012[1] | 0.05 | 0.00 | 0.02 | 0.00 | 0.03 | 0.00 | 0.02 | 0.00 |

[1]IBLI was not sold during these seasons.

*Appendix C Household characteristics*

**Table C1.** Description of household characteristics used to examine idiosyncratic risk

| **Variable** | **Description** |
|---|---|
| Idiosyncratic Losses | Seasonal difference between household loss rate and division average loss rate. |
| Semi-Variance | Within household sum of squares of the difference between losses and covariate losses, conditional on individual losses greater than covariate losses. |
| Age | Age of head of household to capture lifecycle and herding experience effects. |
| Household Size | Number of individuals in the household as a control for access to labor. |
| Dependency Ratio | The ratio of persons under 15, over 65, chronically ill, and disabled to total household members. |
| Asset Index | An index constructed by factor analysis of a large list of household construction materials and assets. The asset index is discussed in more detail below. |
| HSNP | A dummy variable indicating that the household is a participant in the Hunger Safety Net Program (HSNP), an unconditional cash transfer program. |
| % Camels | Ratio of herd that are camels |
| % Cattle | Ratio of herd that are cattle |
| Herd Size | Total herd size in tropical livestock units (TLU) where Camel=1TLU, Cattle=0.7<br><br>TLU, Sheep or goats=0.1 TLU |
| Income | Total cash and in-kind income in real (February 2009) Kenya shillings adjusted for changes to the consumer price index found at Kenya National Bureau of Statistics. |
| Ratio Income Livestock | Share of income generated from livestock and their byproducts. |
| Savings | Total savings in real (February 2009) Kenya shillings adjusted for changes to the consumer price index found at Kenya National Bureau of Statistics. |
| Social Groups | A count of the number of the following groups that the household participates in: self-help group, women's group, youth group, group related to a water point, group related to pasture, group related to livestock business, merry-go-round savings and lending group, and other. |
| Risk Aversion | Risk aversion is elicited by offering a one-time lottery similar to the process described in Binswanger (1980). Each household choose one lottery, a coin was flipped, and the household received payment accordingly. The households were given the following set of gambles to choose from:<br>A: Heads- 50 KSH , Tails – 50KSH; B: Heads- 45 KSH , Tails – 95KSH;<br>C: Heads- 40 KSH , Tails – 120KSH; D: Heads- 30 KSH , Tails – 150KSH;<br>E: Heads- 10 KSH , Tails – 160KSH; F: Heads- 0 KSH , Tails – 200KSH;<br><br>In this analysis, household's level of risk aversion is categorized according to their lottery choice by the following: A or B are considered extremely risk averse, C or D are moderately risk averse, E or F are extremely risk averse. |

**Table C2.** Summary statistics of idiosyncratic risk and household characteristics

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Idiosyncratic Losses | 0.00 | 0.19 | -0.44 | 0.95 |
| Semi-Variance of Idiosyncratic Losses | 0.036 | 0.038 | 0.001 | 0.258 |
| | | | | |
| Age of household head | 47.59 | 18.55 | 18 | 99 |
| Number of household members | 5.53 | 2.11 | 1 | 19 |
| Dependency ratio | 0.60 | 0.20 | 0 | 1 |
| HSNP participant (1=yes) | 0.23 | 0.42 | 0 | 1 |
| Ratio of herd: camels | 0.28 | 0.31 | 0 | 1 |
| Ratio of herd: cattle | 0.32 | 0.31 | 0 | 1 |
| Herd size (TLU) | 14.02 | 19.42 | 0 | 344.08 |
| Income (Ksh/month) | 6,958 | 10,893 | 0 | 236,039 |
| Ratio income from livestock | 0.67 | 0.42 | 0 | 1 |
| Savings (Ksh) | 2,918 | 26,816 | 0 | 1,515,152 |
| Number of social groups | 0.56 | 0.80 | 0 | 6 |
| Extremely Risk Averse[1] | 0.279 | | 0 | 1 |
| Moderately Risk Averse[1] | 0.493 | | 0 | 1 |
| Risk Neutral/Low Risk Aversion[1] | 0.228 | | 0 | 1 |

[1]Dummy variable =1 if true.

The asset index is constructed using factor analysis of a list of important household assets and characteristics in the spirit of Sahn and Stifel (2000). Included are counts of assets that fall into very small, small, medium, and large assets. Small, medium, and large categories are also each divided into two categories according to use (e.g., productive vs. other). There are also indicators of water source, household construction, lavatory facilities, fuel sources, education, cash on hand, land holdings, poultry, and donkeys. Cattle, camels, goats, and sheep are not included in the index as they are captured directly in herd size. The factor loadings are found in Table C3.

**Table C3.** Factor loadings estimated by factor analysis and used to generate an asset index

| Variables | Factor Loading |
|---|---|
| Improved Wall | 0.1324 |
| Improved Floor | 0.1302 |
| Improved Toilet | 0.1285 |
| Improved Light | 0.1178 |
| Improved cooking appliance | 0.0766 |
| Improved Fuel | 0.0643 |
| Improved furniture | 0.1650 |
| Water Source: Open | 0.0039 |
| Water Source: Protected | 0.0042 |
| Water Source: Borehole | -0.0082 |
| Water source: Tap | 0.0398 |
| Water Source: Rainwater catchment | 0.0792 |
| Water Source: Tanker | 0.0214 |
| Education | 0.1214 |
| Total cash savings | 0.0851 |
| Land | 0.0511 |
| Irrigation | 0.0331 |
| Poultry | 0.0814 |
| Donkeys | 0.0188 |
| Very small | 0.0397 |
| Small tools | 0.1263 |
| Small other | 0.0531 |
| Medium tools | 0.1636 |
| Medium other | 0.1351 |
| Large | 0.0373 |
| Large with motor | 0.0891 |

Division-period dummies included in factor analysis.

*Appendix D: First differences robustness check*

**Table D1.** Fixed effects regression of factors that contribute to idiosyncratic livestock mortality losses

| VARIABLES | Idiosyncratic Losses |
|---|---|
| Household size | 1.453 |
| | (1.525) |
| Dependency ratio | 0.0157 |
| | (0.0757) |
| Asset index# | -0.0158 |
| | (0.2961) |
| Asset index squared# | 0.7824 |
| | (0.7600) |
| HSNP participant | -0.0164 |
| | (0.0161) |
| % herd camels& | 0.0274 |
| | (0.0443) |
| % herd cattle& | 0.0137 |
| | (0.0473) |
| Herd size (TLU/100)& | -0.1072 |
| | (0.1484) |
| Herd size$^2$ (TLU$^2$/100$^2$)& | 0.0519 |
| | (0.1912) |
| Herd size$^3$ (TLU$^3$/100$^3$)& | -0.0301 |
| | (0.0584) |
| Ratio income from livestock# | -0.0260 |
| | (0.0192) |
| Savings (KSH/1,000)# | 0.0053* |
| | (0.0029) |
| Social groups count# | -0.0041 |
| | (0.0144) |
| Constant | -0.0783 |
| | (0.0995) |
| Observations | 5,117 |
| Number of households | 735 |
| R-squared | 0.025 |

#Variable is lagged by one period in order to reduce potential endogeneity. &Variable uses seasonal average monthly herd size. Cluster-robust standard errors in parenthesis. *** p<0.01, ** p<0.05, *p<0.1

*Appendix E: Factors that contribute to net benefits due to IBLI coverage*

Although the focus of this paper is to decompose basis risk in order to examine the factors that drive each of its components, policy makers may be more interested in how those factors net out to drive net benefits. A thorough examination of the impacts of IBLI on household welfare falls well beyond the scope of this paper (see Jensen, Mude & Barrett 2014 for such an analysis) but we can use the processes used in this paper to examine idiosyncratic risk to also examine the factors that contribute to net improvement to outcomes. Here, as above, we define household period outcomes without insurance as the livestock mortality rate and the outcome with insurance as the net of livestock mortality rates, premiums paid, and indemnity payments received. The loaded unsubsidized seasonal premium rate is used here.

Our variable of interest is then the reduction to risk due to insurance coverage. If we assume that households are risk averse, they place more weight on marginal differences to large shocks than small shocks, which we approximate by squaring the outcome variable. Because squaring suppresses the distinction between overpayments and underpayments, the period specific net outcome is restricted to be greater than or equal to zero.[33] The average of the difference of the eight period sum of squares (equation E1), is then our approximation of benefits.

(E1) $$Benefit_{id} = \frac{1}{T-1}\left\{\sum_{t=1}^{T}(M_{idt})^2 - (\max[M_{idt} + Premium_{idt} - Indemnity_{idt}, 0])^2\right\}$$

To determine the factors that contribute to level of net benefits, we perform an analysis similar to that found in columns (4)-(6) in Table 9 but also include an analysis only controlling for index division fixed effects. We expect that the factors that are associated with improved net benefits to be those that are either correlated with idiosyncratic risk or those that are associated with design risk. Because design risk is determined at the division level, any household characteristic that contributes significantly to net benefits but not to

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[33] This definition is the same as semi-variance described in the body of the text, placing the target at zero and the indicator function is equal to one if the period specific net outcome is greater than zero and zero otherwise.

idiosyncratic risk is likely to be a reflection of regional differences between households, such as ethnicity and related herding practices or access to environmental services.

The estimates can be found in Table E1. Division level fixed effects capture over 35% of the variation in benefits between households. According to the earlier analysis of design risk, we do expect that there is significant and large differences between the accuracy of the index across divisions. It is not surprising that variation in index accuracy plays on as variation in average benefits. In both the design risk analysis and in this benefit analysis, IBLI performs much better in Central/Gadamoji and Maikona divisions than in Laisamis or Loiyangalani.

**Table E1.** Factors associated with net benefits (reduction to semi-variance) due to IBLI coverage

| | $Benefit_{id}$ | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| Age (/100) | | | 0.0451** | 0.0188 |
| | | | (0.0179) | (0.0140) |
| $Age^2$ ($age^2/100^2$) | | | -0.0403*** | -0.0167 |
| | | | (0.0146) | (0.0120) |
| Gender (=1 if male) | | | 0.0014 | 0.0004 |
| | | | (0.0013) | (0.0013) |
| Household size (count/100) | | | -0.0141 | 0.0054 |
| | | | (0.0326) | (0.0249) |
| Dependency ratio | | | -0.0057* | -0.0061** |
| | | | (0.0034 | (0.0027) |
| Asset index (/10) | | | 0.0068 | -0.0257* |
| | | | (0.0146) | (0.0154) |
| Asset $index^2$ ($/10^2$) | | | -0.0308 | -0.0061 |
| | | | (0.0524) | (0.0442) |
| HSNP participant | | | -0.0014 | 0.0021* |
| | | | (0.0012) | (0.0013) |
| Ratio herd camels | | | 0.0007 | -0.0072** |
| | | | (0.0034) | (0.0032) |
| Ratio herd cattle | | | 0.0027 | -0.0042 |
| | | | (0.0058) | (0.0040) |
| Herd size (TLU/100) | | | 0.0104 | 0.0436*** |
| | | | (0.0153) | (0.0151) |
| Herd $size^2$ ($TLU^2/100^2$) | | | -0.0254 | -0.0776*** |
| | | | (0.0294) | (0.0293) |
| Herd $size^3$ ($TLU^3/100^3$) | | | 0.0168 | 0.0401*** |
| | | | (0.0140) | (0.0142) |
| Ratio income from livestock | | | -0.0131*** | -0.0023 |
| | | | (0.0030) | (0.0037) |
| Log (1+Savings) | | | -0.0001 | 0.0003 |
| | | | (0.0003) | (0.0003) |
| Social groups (count) | | | 0.0012 | 0.0008 |
| | | | (0.0011) | (0.0011) |
| Moderately risk averse | | | -0.0006 | 0.0008 |
| | | | (0.0014) | (0.0012) |
| Extremely risk averse | | | 0.0017 | 0.0018 |
| | | | (0.0015) | (0.0013) |
| | | | | |
| Division Fixed Effects (4) | Yes | No | No | No |
| Sublocation Fixed Effects (16) | No | Yes | No | Yes |
| F-stat testing: All location fixed effects=0 | 39.88 | 17.30 | | 7.486 |
| | | | | |
| Observations | 735 | 735 | 735 | 735 |
| R-squared | 0.289 | 0.348 | 0.183 | 0.401 |

Regression also included an intercept term. * Household clustered-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Moving to the fixed effects to the sublocation level accounts for an additional 5.9% of the variation in benefits, indicating that there is some within division variation in benefits but most of the geographically defined variation takes place between index divisions.

As expected from the idiosyncratic risk analysis, household characteristics contribute very little to net benefits. Placing these findings in the context of our decomposition of basis risk, the majority of the basis risk or net benefits associated with IBLI coverage cannot be easily attributed to any of the household characteristics that we observe. Rather, it seems that the portion of net benefits (or basis risk) that we can account for are due to significant design risk in the product and losses that are correlated at a smaller geographic scale than the index scale. The remaining idiosyncratic component seems to be mostly random.

# Chapter 3: How Basis Risk and Spatiotemporal Adverse Selection Influence Demand for Index Insurance

Co-Authored with Andrew G. Mude and Christopher B. Barrett.

## Introduction

Risk management interventions have become a priority for development agencies as the enormous cost of uninsured risk exposure, especially to the rural poor, has become increasingly widely appreciated. Improved risk management through innovative insurance products is hypothesized to crowd in credit access, induce investment, support informal social transfers, and generally stimulate growth and poverty reduction (Hess et al. 2005; Skees, Hartell & Hao 2006; Barrett et al. 2007; Barnett, Barret & Skees 2008; Boucher, Carter & Guirkinger 2008; Skees & Collier 2008; Giné & Yang 2009; Hellmuth et al. 2009; Karlan et al. 2014). Although insurance products offer a proven means to manage risk through formal financial markets, the asymmetric information problems—adverse selection and moral hazard—and high fixed costs per unit insured effectively preclude conventional indemnity insurance for smallholder crop and livestock farmers in developing countries.

Index insurance products have flourished over the past decade as a promising approach to address these obstacles. Index insurance products use easily observed, exogenous signals to provide coverage for covariate risk. Anchoring indemnity payments to external indicators, not policyholder's realized losses, eliminates the need to verify claims, which is particularly costly in remote areas with poor infrastructure and clients with modest covered assets, and mitigates the familiar incentive challenges associated with moral hazard and adverse selection that plague traditional insurance. These gains do come at the cost, however, of "basis risk", defined as the residual risk born by insurees due to the imperfect association between experienced losses and indemnification based on index values. Furthermore, a form of adverse selection may remain if prospective purchasers have information about upcoming conditions that affect insured, covariate risk – such as climate forecasts – but that information is not incorporated into the index insurance product's pricing (Carriquiry & Osgood 2012).

The explosion of interest in index insurance has resulted in a proliferation of pilot programs across the developing world. A burgeoning literature addresses various aspects of theoretical and applied concerns in the design, implementation, and assessment of index insurance products (e.g., Barnett & Mahul 2007; Barrett et al. 2007; Binswanger-Mkhize 2012; Chantarat et al. 2007; Clarke 2011; Miranda & Farrin 2012). Despite the celebrated promise of index insurance, uptake in pilot programs around the globe has been far below anticipated levels, and there are as of yet no examples of clear success stories with demonstrable capacity for scalability or sustainability over the long run (Smith & Watts 2010; Hazell & Hess 2010; Leblois & Quiron 2010). As a result, most empirical research on index insurance in developing countries has focused on identifying the barriers to insurance uptake. Although demand appears to be price sensitive, as expected, studies find considerable variation in the price elasticity of demand, ranging from -0.44 to -1.16 (Mobarak & Rosenzweig 2012; Cole et al. 2013; Hill, Robles & Ceballos 2013). And, with the exception of the Ghanaian farmers studied by Karlan et al. (2014), uptake has been low even at heavily subsidized prices.[34] With evidence that price plays only a small part in determining demand, researchers have turned to examining the role of non-price factors. Risk aversion, wealth, financial liquidity, understanding of the product, trust in the provider, and access to informal risk pooling commonly exhibit significant, although sometimes inconsistent, impacts on demand (Giné, Townsend & Vickery 2008; Chantarat et al. 2009; Pratt, Suarez & Hess 2010; Cai, de Janvry & Sadoulet 2011; Clarke 2011; Janzen, Carter & Ikegami 2012; Liu & Myers 2012; Mobarak & Rosenzweig 2012; Cole et al. 2013; McIntosh, Sarris, & Papadopoulos 2013; Dercon et al. 2014).

[34] The high demand for rainfall insurance in Ghana is somewhat of a mystery. Karlan et al. (2014) point to the role that insurance grants and indemnity payments play, but those same processes have been observed elsewhere unaccompanied by similar high levels of demand.

Although basis risk and the possibility of spatiotemporal adverse selection are widely understood as prospective weaknesses of index insurance, the empirical research has thus far not directly explored the role that either of these factors plays in influencing product uptake. But if the insurance index is imperfectly correlated with the stochastic welfare variable of interest (e.g., income, assets), then index insurance may offer limited risk management value; indeed it can increase, rather than decrease, purchasers' risk exposure (Jensen et al. 2014). Furthermore, prospective purchasers may perceive that an index insurance product is mispriced for their specific location or for the upcoming season, given information they have on covariate risk for the insured period and place.

Both of these problems exist generally in index insurance contracts and either should adversely affect uptake. A recent review of index insurance pilots concludes, "[g]iven the central role played by basis risk in determining benefits of and demand for index insurance, at least some modest efforts should be made to assess its magnitude" (Miranda & Farrin 2012, p.422). Yet the impact of these prospective weaknesses in index insurance products has not been carefully researched to date, although a few studies use coarse proxies for idiosyncratic risk (e.g., Karlan et al. 2014; Mobarak & Rosenzweig 2012). This lacuna arises primarily because the vast majority of products fielded to date remain unable to determine the level of basis risk inherent in their product design; the products were designed from data series on index variables (e.g., rainfall, crop growth model predictions), not from longitudinal household asset or income data from the target population to be insured.

This paper fills that gap, exploiting an unusually rich longitudinal dataset from northern Kenya and the randomization of inducements to purchase index-based livestock insurance (IBLI), a product designed from household data to minimize basis risk (Chantarat et al. 2013), in order to identify the impact of basis risk and spatiotemporal selection on index insurance uptake. We further distinguish between the two central components of basis risk, design error – associated with the imperfect match between the index and the covariate risk the index is meant to match – and idiosyncratic risk – individual variation around the covariate experience. Design error can be reduced by improving the accuracy of the index, while idiosyncratic risk inherently falls outside the scope of index insurance policies. We find that both spatiotemporal selection and basis risk are important and, in particular, that although correctable design error plays a role, the main demand effects arise due to idiosyncratic risk intrinsic to any index insurance product.

Using longitudinal seasonal and annual household survey data collected over four years, we follow demand over multiple seasons as households learn about the product and the basis risk components that they face. Notably, uptake was healthy during the first sales window (27.8% of the sample purchased), but has dropped off rather dramatically in the following sales periods. Echoing the prior literature, we find that price, liquidity, and social connectedness affect demand in the expected ways. In addition, we find that basis risk and spatial adverse selection associated with division average basis risk dampen demand for IBLI. Households in divisions with greater average idiosyncratic risk are much less likely to purchase any insurance than those in divisions with relativity more covariate risk. Among those that do purchase and that experienced an exogenous increase in understanding of the IBLI product due to randomized educational interventions, increased idiosyncratic risk is negatively related to quantity of coverage purchased. Design error also plays a role in demand, reducing uptake and increasing price sensitivity among those who purchase coverage. But, between the two components of basis risk, design risk plays a much smaller role, reducing uptake by an average of less than one percent (average marginal effect [AME] =-0.0067, Std. Err.= 0.0029) while the division average covariance between individual and covariate losses effects uptake by nearly 20% on average (AME = 0.1924, Std. Err.=0.0379). Consequently the basis risk problem is not easily overcome through improved product design. There is also strong evidence of intertemporal adverse selection as household purchase less coverage, conditional on purchasing, before seasons for which they expect good conditions (AME=-0.2646, Std. Err.=0.1086). This impact represents an 8% reduction in average demand among those purchasing.

The remainder of the paper is organized as follows. Section 2 discusses risk among pastoralists and the motivation for and design of the IBLI product offered to them. Section 3 develops a stylized model of livestock ownership and the role of insurance so as to understand the structural determinants of demand. Section 4 presents the research design and data followed by an explanation and summary of key variables in Section 5. Section 6 describes the econometric strategy used to analyze demand for IBLI. The results are discussed in Section 7.

## Drought-Related Livestock Mortality & Index Insurance in Northern Kenya

A first order concern in the design of an optimal insurance index is that it significantly reduces risk borne by the target population and that the index covaries strongly with observed losses. The IBLI Marsabit product expressly covers predicted area average livestock mortality due that arise due to severe forage shortages associated with drought precisely because drought-related livestock mortality has consistently emerged as the greatest risk faced by pastoralists in the arid and semi-arid lands (ASAL) of the Horn of Africa (McPeak & Barrett 2001; McPeak, Little & Doss 2012).

Livestock not only represent the principal source of income across most ASAL households (mean=70% and median=100% in our data) but also constitute the highest value productive asset they own. Livestock face considerable mortality risk, rendering ASAL households particularly vulnerable to herd mortality shocks. Among these, drought is by far the greatest cause of mortality, and drought-related deaths largely occur in times of severe forage shortages. For example, between June 2000 and June 2002, surveyed pastoralists reported that drought-related factors accounted for 53% of the livestock deaths that they experienced, and disease, which is often associated with droughts, caused an additional 30% mortality during that period (McPeak, Little & Doss 2012). Drought is the cause of 47% of livestock mortality in our

2009-12 sample from northern Kenya. Droughts represent a covariate risk that may be especially difficult for existing social risk pooling schemes to handle because losses can impact all members of the risk pool. At the same time, the seemingly largely covariate risk profile pastoralists face seems well-suited for coverage by an index product.

Launched in January 2010 in the arid and semi-arid Marsabit District to address the challenge of drought-related livestock mortality, the index based livestock insurance (IBLI) product is derived from the Normalized Difference Vegetation Index (NDVI), an indicator of photosynthetic activity in observed vegetation as reflected in spectral data remotely sensed from satellite platforms at high spatiotemporal resolution (Chantarat et al. 2013). These NDVI data are reliably and cheaply accessible in near real-time, and with sufficiently long historical record to allow for accurate pricing of the IBLI product (Chantarat et al. 2013). The statistical relationship between NDVI and livestock mortality was estimated using historic household level livestock mortality rates and NDVI values from January 2000 through January 2008 and then tested out-of-sample against a different set of seasonal household panel data collected 2000-2 in the same region.[35] The resulting response function generates estimates of division average livestock mortality rate on the basis of NDVI inputs.[36] IBLI appears to be the only index insurance product currently on the market that was developed using longitudinal household data so as to minimize the design component of basis risk.[37]

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[35] Monthly household-level livestock mortality data were collected by the Arid Lands Resource Management Project (ALRMP, http://www.aridland.go.ke/). The seasonal household panel data used for out-of-sample evaluation come from the Pastoral Risk Management project (http://dyson.cornell.edu/special_programs/AFSNRM/Parima/projectdata.htm).

[36] "Divisions" are existing administrative units in Kenya that IBLI has used to define the geographic boundaries of a contract. Division boundaries are suitable because they are large enough to reduce moral hazard to a negligible level, small enough to capture a large portion of covariate risk, and were well known by pastoralists.

[37] An index based livestock insurance program in Mongolia, which protects pastoralists from the risk of severe winters known as dzud, seems to have been designed off area average herd mortality rates (see Mahul & Skees 2007 for a full description of the IBLI Mongolia project). As of writing, the Mongolian program has yet to make its findings public so we are unable to use the similarities between programs to inform this research.

Marsabit region is divided into five index divisions based on existing administrative boundaries. The index is calculated separately for each division allowing for variation between divisions. A commercial underwriter has offered IBLI contracts written on this predicted livestock mortality rate index (see Chantarat et al. 2013 for more details on data and product design). The commercial underwriter choose to set a single strike level at 15% livestock mortality and aggregated the five index divisions into two premium regions. Notably, the aggregation of index divisions into premium regions results in variation in loadings/subsidies between index divisions, opening the door for spatial adverse selection.[38] A detailed summary of the contract parameters (e.g., geographical segmentation of coverage, temporal coverage of the contract, conditions for contract activation, indemnification schedule, pricing structure) is presented in Appendix A.

During the first sales season in January 2010, the IBLI product sold 1,974 policies to cover the long rain/long dry season of 2010 (LRLD10) and following short rain/short dry season (SRSD10), from March 1, 2010-Ferburary 28, 2011. The intention was to have a sales window during the two-month period before the onset of each bimodal rainy season. Due to logistical and contractual complications, IBLI was not available for purchase during the August/September 2010 or January/February 2012 periods. In total, there have been four sales windows and six seasons of coverage during the timeframe considered in this paper. Table 1 presents summary statistics for IBLI sales over the four rounds that fall within our sample period.

There was a consistent fall in IBLI uptake over the 2010-2012 period. Although inconsistency of sales windows, a change in the commercial insurance provider, and variation in extension and sales protocols are likely to have depressed sales, heterogeneity in demand suggests that other factors also influenced purchases. Tracking household purchase patterns across seasons shows considerable variation in when

[38] The aggregation of index divisions into premium regions had been dropped in the newer IBLI products.

households make their first purchase, if they continue to purchase, or if they allow their contract to lapse (Table 2). Such behavior suggests dynamic factors play a significant role in insurance demand. In the next section, we offer a simple model of index insurance demand and examine the role that basis risk and spatiotemporal adverse selection could play in determining demand.

## Demand for Index Based Livestock Insurance

This section sets up a simple model of household demand for insurance that offers a set of empirically testable hypothesis concerning basis risk and spatiotemporal adverse selection. This is meant merely to motivate the empirical exploration that is this paper's primary contribution. So we simplify this as a static problem under uncertainty and ignore dynamical considerations in the interests of brevity.

Let households maximize their expected utility, which is an increasing and concave von Neumann-Morgenstern function that satisfies U'>0, U''<0. Utility has wealth, measured as end-of-period herd size in tropical livestock units (TLU), as its argument.[39] Households have an initial livestock endowment,$TLU_{0,}$ but the herd is subject to stochastic losses (L). Households have the option of purchasing livestock insurance at the rate of $p$ per animal insured ($\widetilde{tlu}$) where $\widetilde{tlu}$ is in units of livestock and $p \in [0,1]$.[40] The insurance makes indemnity payments according to an index, which is the predicted rate of division average livestock losses ($I \in [0,1]$).[41] The utility maximization problem and budget constraint can be described as follows, where E is the expectation operator.

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[39] Tropical livestock units (TLUs) are a conversion rate used to aggregate livestock. The IBLI contracts use the conversion rate of 1 TLU = 0.7 camels = 1 cattle = 10 sheep or goats as suggested by the FAO Livestock and Environment Toolbox (1999).

[40] The premium and index are defined as ratio of the value insured to avoid the need to place a monetary value on livestock. This specification is appropriate in the context of livestock insurance in northern Kenya because households often sell off a small animal in order to purchase insurance on remaining animals. If the cost of insuring one animal was equivalent to the value of the animal, p=1.

[41] The division refers to the geographic region defined by the insurance product.

(1) $$\max_{\widetilde{tlu}} E[U(TLU)],$$

$$subject\ to: TLU = TLU_0 - L - \widetilde{tlu} * p + \widetilde{tlu} * I$$

Normalize the variables $TLU, TLU_0, L, \widetilde{tlu}$ by $TLU_0$ so that they are now all expressed as proportions of the household's initial herd endowment. Substituting the budget constraint into the utility function and using a second order Taylor expansion allows us to approximate the expected utility maximization problem as a function of original livestock endowment and deviations from the endowment associated with losses, premium payments and indemnity payments.[42] The necessary first order condition becomes

(2) $$E\left[U'(TLU_0)(-p+I) + U''(TLU_0)\left[Lp - L*I + \widetilde{tlu}*p^2 - 2p*I*\widetilde{tlu} + \widetilde{tlu}*I^2\right]\right] = 0$$

The first order condition can be solved for optimal insurance purchases. We use the representations $E[x] = \bar{x}$, $Cov(x,y)$= the covariance of $x$ and $y$, and $Var(x)$ = variance of $x$, where $x$ and $y$ are representative variables. In addition, we use U=U(TLU$_0$) to reduce character burden. With some algebra, the optimal number of animals to ensure can be written as equation (3).

(3) $$\widetilde{tlu}^* = \frac{U''[\bar{L}(\bar{I}-p) + Cov(I,L)] - U'(\bar{I}-p\ )}{U''\left((\bar{I}-p)^2 + Var(I)\right)}$$

If premiums are actuarially fairly priced, then the premium rate is equal to the expected index value ($\bar{I} =$

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[42] $\max_{\widetilde{tlu}} E\left[U(TLU_0) + U'(TLU_0)\left(-L - \widetilde{tlu}*p + \widetilde{tlu}*I\right) + \frac{1}{2}U''(TLU_0)\left(-L - \widetilde{tlu}*p + \widetilde{tlu}*I\right)^2\right]$

$p$). In that case, optimal coverage is $\widetilde{tlu}^* = \frac{Cov(I,L)}{Var(I)}$, which is greater than zero as long as the covariance between the index and losses is positive. If the insurer adds loadings to the policy premium so that $\bar{I} < p$, then optimal insurance purchase volumes can be zero even when the index is positively correlated with household losses.

***Basis risk***

If there is no basis risk ($cov(I, L) = Var(I)$) and the premiums remain actually fair, then the index and losses are identical and $\widetilde{tlu}^* = 1$, i.e., full insurance is optimal. As the covariance between the index and individual losses falls, however, so does optimal coverage ($\frac{d\,\widetilde{tlu}^*}{dCov(I,L)} = \frac{1}{Var(I)} > 0$).

To more closely examine the role that basis risk plays, let the index equal individual losses multiplied by a coefficient, a constant, and a random error term ($I = \beta_0 + \beta_1 L + \varepsilon$). The expected difference between the index and losses (expected basis error) is captured by the relationship $\beta_0 + \beta_1 L$, in particular deviations from the null $\beta_0 = 0$ and $\beta_1 = 1$, while $Var(\varepsilon)$ is the variance in basis error.

Because the covariance between the error term and losses is zero by construction, optimal coverage for actuarially fairly priced index insurance with basis risk is $\widetilde{tlu}^* = \frac{\beta_1 Var(L)}{\beta_1 Var(L) + Var(\varepsilon)}$. Clearly, as the variance in basis error increases, demand falls. Alternatively, as $\beta_1$ increases so does demand as long as there is some variance in basis error ($Var(\varepsilon) \neq 0$).[43] At actuarial fair premium rates with no variance in basis error, households can adjust their purchase levels to account for expected basis error at no change to expected net costs, and full coverage continues to be optimal.

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[43] $\frac{d\widetilde{tlu}}{d\beta} = \frac{var(L)*Var(\varepsilon)}{\left(\beta_1 Var(L)+Var(\varepsilon)\right)^2} \geq 0$. There is a discontinuity in demand where $\beta_1 = -\frac{Var(\varepsilon)}{Var(L)}$ but demand is increasing with $\beta_1$ on either side of the discontinuity.

Relaxing the premium constraint, let premiums be set so that $p + \delta = E[I]$, where $\delta$ represents the net loading on the policy, reflecting any subsidy to purchasers less than loading above actuarially fair rates (i.e., expected indemnity payments) by the underwriter. Thus, if there is a net subsidy, $\delta > 0$, while if the premiums are loaded beyond the subsidy, $\delta < 0$. Optimal coverage is not monotonic in premium rates because changes to premium rates not only effect the opportunity cost of premium payments but also have wealth effects that are ambiguous in the impact on demand ($\frac{\partial \widetilde{tlu}^*}{\partial \delta} = \frac{\{U''\bar{L} - U'\}}{D} - \frac{2\delta U''\{U''[\bar{L}(\delta) + \beta_1 Var(L)] - U'(\delta)\}}{D^2}$). Clarke (2011), discusses a similar outcome.

Adjusting the earlier model with basis risk to allow for variation in premium rates, optimal coverage is now $\widetilde{tlu}^* = \frac{U''[\bar{L}(\delta) + \beta_1 Var(L)] - U'(\delta)}{[U''((\delta)^2 + \beta_1 Var(L) + Var(\varepsilon))]}$ and demand still falls with increased variance in basis error.[44] The importance of basis risk might also change with prices. Analytically, we find that demand response to basis risk changes with premium rates but is also subject to the ambiguous wealth effects (equation 4).

(4)
$$\frac{\partial^2 \widetilde{tlu}^*}{\partial p \partial Var(\varepsilon)} = \frac{U''(U' - U''\bar{L})}{D^2} + \frac{4U''^2 \delta N}{D^3} \leq 0$$

Where $D = U''[\delta^2 + \beta_1 Var(L) + Var(\varepsilon)]$ and $N = U''[L\delta + \beta_1 Var(L)] - U'\delta$. This leads to

*Hypothesis 1: As basis risk grows, demand falls, and that response changes with premium levels.*

We also expect that the impact of the premium changes with basis risk in the same direction as $\frac{\partial^2 \widetilde{tlu}^*}{\partial p \partial Var(\varepsilon)}$ due to symmetry of cross partials in the Hessian matrix. This is consistent with Karlan et al.'s (2014) finding that households were less responsive to price incentives in regions with low product quality (high design

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[44] $\frac{\partial \widetilde{tlu}^*}{\partial var(\varepsilon)} = -\frac{U''\{U''[\bar{L}(\delta) + \beta_1 Var(L)] - U'(\delta)\}}{D^2} \leq 0$

error).

In some cases it may be that households do not understand the insurance product well. For example, a household might think that the insurance product indemnifies all losses or that indemnity payments are always made at the end of every season. In either of these cases, basis risk should play no role in the purchase decision, although it could have a large impact on the eventual welfare outcomes of the purchase decision. Between those two extremes, there may be households that partially understand the insurance contract but have some misconceptions. Let an individual's understanding of the product be summarized by the term ($I_i = I + z_i$) where $I$ continues to the index that determines indemnity payments, $z_i$reflects the individual's misinformation and $I_i$ is the index required to produce the indemnity payment that the individual expects to receive. Assuming actuarially fair premium rates, the optimal purchase is $\widetilde{tlu}^* = \frac{Cov(I,L)+Cov(z,L)}{Var(I)+Var(z)+2*Cov(I,z)}$. If the misconceptions are negatively and highly correlated with the index, the consumer's optimal purchases could increase with increased basis risk.[45] Otherwise, households with misconceptions reduce optimal purchases with increased basis risk but that response is mitigated by basis risk.[46] This relationship leads to our next hypothesis:

*Hypothesis 2: Poor understanding of the product moderates the negative demand response to increases in basis risk. At the most extreme levels of misinterpretation of the contracts, households may not respond at all to basis risk or might increase demand with basis risk.*

***Spatiotemporal Adverse Selection***

Indemnifying covariate losses, rather than individual losses, eliminates the prospective impact on insurer

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45 $\frac{d\,\widetilde{tlu}^*}{dCov(I_i,L)} = \frac{1}{Var(I)+Var(z)+2*Cov(I,z)} < 0$ if $Var(I) + Var(z) + 2 * Cov(I,z) < 0$

46 $\frac{d\,\widetilde{tlu}^*}{dCov(I_i,L)} < \frac{d\,\widetilde{tlu}^*}{dCov(I,L)}$ if $Var(z) + 2 * Cov(I,z) > 0$

profits of within index-division cross-sectional adverse selection by decoupling indemnity payments from individual losses.[47] But group-level adverse selection can reemerge if households have information on the likelihood of an indemnity payment in the coming season that is not reflected in the premium. For example, ecological conditions during the sales window may have predictive power as to the likelihood of an upcoming drought. In this case, the consumer has a signal (observed ecological conditions) that provides information on the distribution of coming average losses and thus the likelihood of indemnity payments, and that information was not incorporated in the product's pricing. Even in cases when the insurer can observe the same information that households can, contracts are not always written with variable premium rates. Rather, insurers and reinsurers often set prices according to historic averages and are commonly reluctant to change premiums season by season.

Such intertemporal adverse selection can be incorporated into the above model. Assume that a household observes a signal before purchasing insurance that provides information on the likelihood of certain end-of-season rangeland conditions that could affect the index for this specific season ($E$[I]) and/or the mortality rate at the end of this season ($E[L^{*}]$). Let $x^{*}$ be the household's interpretation of the signal as an adjustment to the index $[I^{*}] = E[I] + x^{*}$ and $y^{*}$be the household's interpretation of the signal as an adjustment to her own expected livestock mortality rate ($E[L^{*}] = E[L] + y^{*}$) where $x^{*}, y^{*} \in [-1,1]$. We can then rewrite 3 as (3').

(3‘)
$$\widetilde{tlu} = \frac{U''[(\bar{L} + y^{*})(\bar{I} + x^{*} - p) + cov(I, L)] - U'(\bar{I} + x^{*} - p\ )}{[U''\big((\bar{I} + x^{*} - p)^{2} + Var(I)\big)]}$$

[47] For the same reasons, index insurance reduces the incentives for moral hazard.

If the signal pertains only to individual losses ($x^* = 0$) , $\frac{d\widetilde{tlu}}{dy^*} = \frac{\bar{I}-p}{\left((\bar{I}-p)^2+Var(I)\right)}$ which signs with $\bar{I} - p$ and is identical to a change in long-run livestock losses ($\bar{L}$). Households that believe they will lose livestock at a greater rate in the following season will increase purchases if premiums are subsidized and reduce purchases if premiums are loaded. This leads directly to our third core, testable hypothesis:

*Hypothesis 3: Households will respond to signals of increased losses by increasing purchases if premiums are below the actuarially fair rate.*

By contrast, if the signal pertains only to the expected index, the outcome is similar to changes in loadings/subsidies and is not monotonically increasing or decreasing in $x^*$.[48] But, just as with the ambiguous impact of premium rates on optimal purchases, we can learn about impact of $x^*$ through its impact on $\frac{d\widetilde{tlu}}{dy^*}$. The cross partial, $\frac{\partial^2 \widetilde{tlu}^*}{\partial x^* \partial y^*} = \frac{U''^2[Var(I)-(\bar{I}+x-p)^2]}{\left[U''\left((\bar{I}+x^*-p)^2+Var(I)\right)\right]^2}$, signs with $Var(I) - (\bar{I} + x - p)^2$. If, for example, $\bar{I} = p$ and the household receives a signal of increased losses and higher index, then $\frac{d\widetilde{tlu}}{dy^*} > 0$ and $\frac{d\widetilde{tlu}}{dy^*}$ increases with $x^*$ until ${x^*}^2 = Var(I)$ and then $\frac{\partial^2 \widetilde{tlu}^*}{\partial x^* \partial y^*} \leq 0$. As with the effects of premiums on demand, the impact of signals that inform on both losses and index levels is an empirical question. If those signals correctly predict coming conditions, such behavior will be evident in a correlation between demand and index value.

A related, spatially defined form of group-level adverse selection can occur when index performance or the difference between the expected index value and the premium varies between distinct geographic regions.[49] Differences between expected indemnity payments and the premium are likely to be common for products with little data with which to estimate the expected indemnity payment. It is, in essence, variance in

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48 $\frac{\partial \widetilde{tlu}^*}{\partial x^*} = \frac{\{U''\bar{L}-U'\}}{U''\left((\bar{I}+x^*-p)^2+Var(I)\right)} - \frac{2(\bar{I}+x^*-p)U''\{U''[(\bar{L}+y^*)(\bar{I}+x^*-p)+cov(I,L)]-U'(\bar{I}+x^*-p)\}}{\left[U''\left((\bar{I}+x^*-p)^2+Var(I)\right)\right]^2}$

49 Within geographic regions there may be clusters of households for whom the index performs especially well or poorly. Although the resulting variation in demand would likely have a geographic component, the within-division demand patterns have no impact on provider's profits and thus is not adverse selection.

subsidy/loading rates between divisions caused by error in the provider's estimated expected index values or perhaps intentionally (e.g., variation in state subsidy rates). This type of spatial adverse selection is covered in the above examination of the effects of varying the subsidy/loadings.

A second type of spatial adverse selection can occur if there is variation in the basis risk between index regions. That is, there may be very little basis risk in one division and a great deal in another even as subsidy/loading rates are similar. As was shown above, regions with higher basis risk are expected to have less demand, all else being equal. This generates our fourth core hypothesis:

*Hypothesis 4: Division-level variation in basis risk will cause spatial adverse selection apparent in uptake patterns.*

This simple, static model conforms to our expectations of reduced demand with increased basis risk. It predicts that basis risk will be less important for those who do not understand the product well, and that as basis risk increases, the price response will change. In addition the model is easily extended to include factors that may contribute to spatial or temporally associated adverse selection. It predicts that we should expect to see variation in demand within divisions over time that is correlated with rangeland conditions during the sales windows.

## Research Design & Data

Before any public awareness campaign began surrounding the January 2010 launch of the IBLI pilot, the IBLI research team began to implement a comprehensive household survey that annually tracks key parameters of interest such as herd dynamics, incomes, assets, livelihood portfolios, market and credit access, risk experience and behavior, demographics, health and educational outcomes, and more. The initial baseline survey was conducted in October of 2009, with households revisited annually thereafter in the same October-November period. A total of 924 households were sampled across 16 sub-locations of

Marsabit District, selected to represent a broad variation of livestock production systems, agro-ecology, market accessibility and ethnic composition.[50]

A few key elements of the survey design are important to note. Two randomized encouragement treatments were implemented to help identify and test key program parameters on demand. In the first, a sub-sample was selected to play a comprehensive educational insurance game based on the pastoral production system. Participants used role playing and simulations to help learn how IBLI functions in the face of idiosyncratic and covariate shocks. The game was played in three rounds of increasing complexity to help build up a comprehensive knowledge of IBLI. The game was played in nine of the 16 sites among a random selection of half of the sample households in each selected site, and took place just before the launch of sales in January 2010.[51]

The second encouragement is an ongoing price incentive that introduces exogenous variation in premium rates. Discount coupons were randomly distributed to about 60% of the sample before each sales season. The discount provided by the coupons was evenly distributed among 10%, 20%, 30%, 40%, 50% and 60% discount levels. Upon presentation to insurance sales agents, the coupon entitles the household to the relevant discount on premiums for the first 15 TLU insured during that marketing season.[52] The coupons expire after the sales period immediately following their distribution.

The IBLI team also coordinated survey sites to overlap with the Hunger Safety Net Program (HSNP), cash

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[50] This sample was distributed across the 16 sub-locations on the basis of proportional allocation using the Kenya 1999 household population census statistics. There were only two exceptions to this rule: a minimum sample size of 30 households and maximum of 100 households per sub-location. In addition, sampling across each sub-location was also stratified by wealth class based on livestock holdings reported by key informants before the selection process.

[51] See McPeak, Chantarat, & Mude (2010) for a description of the IBLI educational game and its implementation in the field.

[52] Of the nine sample households that purchased insurance for more than 15 TLUs, six used a discount coupon for the first 15TLUs.

transfer program launched by the Government of Kenya in April 2009 that provides regular monthly cash transfers to a select group of target households in the northern Kenya ASAL (Hurrell & Sabates-Wheeler 2013). The regularity and certainty of this cash transfer may impact household liquidity constraints and therefore demand for IBLI. Site selection for IBLI extension encouragement was stratified to include both communities targeted by HSNP and other, nearby communities that were not. Figure 1 displays the project's sample sub-locations across Marsabit and illustrates how they vary in terms of the noted elements of the study design. In a structure ensuring that the joint and individual influence of the IBLI game and HSNP transfers could be empirically identified, sub-locations were grouped into four different categories as shown: one group of HSNP recipients who were "game-encouraged", as explained above, and another group of HSNP recipients that were not selected to play the educational games, and another set of two groups consisting of non-HSNP recipients that were either encouraged with games or not.

This paper uses data from four annual rounds of the IBLI household survey collected in Marsabit region between 2009 and 2012. The attrition rate during this period was less than 4% in each round. An analysis of attrition is found in Appendix B. There are a number of differences between those households who remained in the survey and those who attrited (Table B.1), as well as between those who exited the survey and their replacements (Table B.2). For a discussion of the causes of attrition see ILRI (2012). We control for these characteristics in our analysis to mitigate prospective attrition bias introduced by this selection process, but the rate of exit is low enough and differences small enough that attrition should be of little worry.

## Discussion of Key Variables

IBLI purchases among those surveyed and within the general population across the Marsabit region were greatest in the first sales window and declined in the following periods (Table 1).[53] About 46% of the balanced panel (N=832) purchased IBLI coverage at least once during the four sales periods covered in these data, a relatively high rate of uptake when compared against other index insurance pilots in the developing world. Conditional on purchasing an IBLI policy, the mean coverage purchased among the same sample was 3.15 TLUs or 24% of the average herd size during the sales windows. Table 2 details the frequencies of observed transitions between purchased coverage, existing coverage, and lapsed coverage. Figure 2 illustrates the proportion of the sample that purchased IBLI during each sales window and the level of purchase, conditional on purchasing.

Although existing research, which we discuss in detail below, has already provided a framework by which to understand many of the factors of demand, we are in the unique position to empirically examine the role of basis risk and spatiotemporal adverse selection. Both are thought to impact demand but have not yet been tested using observations of household losses. At the same time, we reinforce previous findings in the literature by including factors that have been found to influence to demand elsewhere. This section discusses the key variables used in the analysis.

***Basis Risk***

Low uptake is often thought to be due to basis risk, although no studies to date have had a direct measure of basis risk with which to test that hypothesis. Here it becomes useful to decompose basis risk into its design and idiosyncratic components. Design risk arises due to differences between predicted and actual division-average livestock mortality while idiosyncratic risk is due to differences between the covariate and individual losses.[54]

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[53] It is important to note that IBLI was not available for purchase during the short rain/short dry (SRSD) 2010 or long rain/long dry (LRLD) 2012 seasons due to logistical failures in the commercial supply channel.

[54] We did not distinguish between design and idiosyncratic risk in Section 3 because it is their combined effect that determines the level of risk that an insured individual retains. Because design risk can be corrected through index modification while idiosyncratic risk cannot, this decomposition is useful.

One might think of design risk as an indicator of contract adherence, so far as it is the result of a deviation between the intended and actual coverage provided by a policy. But, households are unlikely to have information about the accuracy (or inaccuracy) of an index before product introduction. In cases where index products are new, such as in the Marsabit IBLI pilot we study, individuals must learn about design risk as index performance is revealed through observations of published index values. Karlan et al. (2014) find evidence that households change their demand for index insurance as they observe new index values, following a demand pattern consistent with learning about the product.

The difference between the index and covariate losses during seasons that IBLI coverage was available and index values were publicized are used to generate our estimates of perceived or observed design risk. These estimates are a lagged moving average of within-division design error during preceding seasons in which IBLI coverage was available. We assume households expect no design error in the first sales round, which is reasonable in this context considering that extension and education focused on the likelihood of idiosyncratic risk but did not discuss design risk at all. After the first round, households discard their initial naive expectation and update so that their posterior is the average observed design error. They continue to do so in each of the following rounds. Table 3 includes the observed design error estimates as well as the seasons used to make each estimate.

Price surely matters to insurance uptake (Cole et al. 2013, Giné, Townsend & Vickery 2008, Karlan et al. 2014). The effective premium rate is calculated as the natural log of the premium rate after accounting for randomly distributed discount coupons. The effective premium rate is also interacted with observed design error to test the hypothesis that the price elasticity of demand changes with basis risk and to determine the sign of that change.

Although households initially have very little information on index accuracy, they are likely to already be quite familiar with their own historical losses and how those losses relate to the average losses within their division — i.e., their risk and idiosyncratic risk. Households that systematically face high losses that are unrelated to covariate losses are less likely to benefit from even an accurate (i.e., no design error) index product. The variance in livestock mortality rate is a measure of the insurable risk that a households faces. The correlation between individual and covariate losses provides a measure of the how well covariate risk matches household risk, providing an indication of the amount of coverage that an index insurance product with zero basis error could provide. A household with a correlation of one could be fully covered by an area average loss index insurance product like IBLI. As correlations fall from one, idiosyncratic risk increases and index insurable risk falls.

The risk (variance in loss rate) and correlation between an individual's loss rate and their division's average loss rate is estimated using all eight observed seasons to provide an indicator of the idiosyncratic risk that each household is exposed to. Figure 3 provides histograms of the estimated correlation between individual losses and covariate losses in each division. There is clearly a great deal of variation within and between divisions in the individual-covariate loss correlation. Indeed, 11.7% of households have a non-positive correlation, implying that IBLI would be risk-increasing for them despite its insurance label.

In order to accurately incorporate knowledge of idiosyncratic risk into their purchase decision, households must also understand that the IBLI contract is meant to insure only covariate risk. Without that understanding, households might not link purchases with their level of idiosyncratic risk. Ideally an estimate of idiosyncratic risk could be interacted with household understanding of IBLI. Although the IBLI survey does include a simple test of accuracy of IBLI knowledge, that evaluation could not be collected before the first sales period and is likely endogenous to the decision to purchase an IBLI policy. In addition, the survey cycle and IBLI sales windows do not coincide so as to provide unique data for each household in each survey window.

As a proxy for IBLI knowledge, we include a dummy for participation in the randomized education game described in the research design section. Participation in the game had a strongly positive and significant impact on performance on the IBLI knowledge test (Table 4). There is some prospect that game participation leads to purchasing through a mechanism other than knowledge (e.g., trust, a sense of obligation) so that the above test reported in Table 4 captures an increase in knowledge due to purchase rather than due to the educational component of the game. This can be tested by restricting the analysis to only those households who never purchase IBLI. As reflected in the second row of Table 4, among those who never purchase IBLI, participation in the game increased average IBLI knowledge test scores by nearly 40% (p-value<0.001), providing strong evidence that randomized participation in the extension game directly leads to greater IBLI knowledge. The indicator variable for exogenous game participation is therefore interacted with the idiosyncratic risk estimate in order to test the hypothesis that greater understanding of the IBLI contracts impacts consumer response to basis risk.

***Spatiotemporal Adverse Selection***

IBLI specifically is susceptible to intertemporal adverse selection because droughts leading to high livestock mortality are often the result of multiple seasons with poor precipitation so that households may wait until conditions are very poor before purchasing insurance. We include two variables—*Pre-Czndvi* and the household's expectation of rangeland conditions in the coming season—to capture ecological conditions that pastoralists may observe while making their purchase decision

*Pre-Czndvi* is a variable used in the IBLI response function to control for conditions at the beginning of the season and is calculated by summing of standardized NDVI values from the beginning of the previous rainy season until the current sales period. Higher *Pre-Czndvi* indicate greater relative greenness during the rainy season leading up to the current insurance season. Although the index takes *Pre-Czndvi* into account when estimating livestock mortality and premiums could be adjusted to reflect the level of risk at the beginning of a season, the insurer and reinsurer have chosen not to vary premium rates to account for this observed intertemporal variation in livestock mortality risk. *Pre-Czndvi* has a statistically significant and negative relationship with predicted livestock mortality rates (column 1, Table 5). Thus, if households observe the relative greenness that is captured by *Pre-Czndvi*, they could use those observations to help predict coming index values and adjust their purchase accordingly.

A set of dummy variables specify if the household's stated expectations for the coming season's rangeland are good, normal, or bad. Expectation of good or normal rangeland conditions are negatively and statistically significantly correlated with end-of-season index values as is expected if they correctly predicted coming rangeland conditions (column 2, Table 5). Our model predicts that as long as premium rates are below the expected indemnity rate, households expecting higher livestock mortality rates will increase purchases but is ambiguous about the impact of that expectation if it also suggests higher index values.[55]

Households' expectations of rangeland conditions may have information that is captured by the *Pre-Czndvi* variable, which the IBLI providers could account for by adjusting premium rates to match their risk exposure, or the households may be able to observe additional information that is not captured by the remotely observe NDVI. Regressing predicted livestock mortality onto both Pre-Czndvi and household's expectations of coming conditions provides strong evidence that the household's information continues to have significant predictive power even after controlling for the observed Pre-Czndvi seasonal values. The implication is the although IBLI providers could control could reduce the potential for intertemporal

[55] The effective seasonal subsidies (E[indemnity payment rate]-seasonal premium rate) are as follows: Central/Gadamoji 0.0249, Laisamis 0.0171, Loiyangalgani 0.0148, and Maikona 0.017.

adverse selection associated with initial rangeland conditions by adjusting premium rates according to *Pre-Czndvi*, they would continue to face risk of adverse selection from accurate private information held by their potential consumers.

We also test for spatially defined adverse selection, which could emerge due to variation in the subsidy/loading rate in policies or variation in the quality of the policies. Variation in subsidy/loading rate is the result of the aggregation of index divisions into larger premium regions so that lower risk divisions are inadvertently subsidizing the premium rates of higher risk division in the same premium region. Division-average livestock mortality rate and risk (variance in livestock mortality rate) are used to capture division-level differences in risk, and thus actually fair premium rate of a perfect index product. Division average idiosyncratic risk (correlation between livestock mortality rate and covariate livestock mortality rate) provides an estimate of the average levels of basis risk and its importance relative to total risk within each division.

***Additional Key Variables***

Within the standard model of insurance, exposure to risk coupled with risk aversion is the fundamental reason for insurance demand. At any level of positive exposure to risk, the benefits of indemnified losses increase with level of risk aversion. But the impact of risk aversion on demand is somewhat ambiguous when market imperfections, such as basis risk or premium loadings, enter the picture. Clarke (2011) shows that for individuals with constant absolute or relative risk aversion, demand for insurance with actuarially unfavorable (favorable) premiums should increase (decrease) and then decrease (increase) as risk aversion increases. Most empirical studies of index insurance demand assume a monotonic relationship between risk aversion and demand, often finding that increased risk aversion is associated with decreased demand (i.e., Giné, Townsend & Vickery 2008; Cole et al. 2013). This negative correlation between risk aversion and demand for insurance has been interpreted as evidence that index insurance uptake in developing countries is more similar to technology experimentation/adoption than to neoclassical models of insurance demand. Hill, Robles, and Ceballos (2013) specifically test for hump-shaped demand across risk aversion as predicted by Clarke (2011), but find no significant difference in demand across the domain of observed risk aversion. In a setup similar to that used by Hill, Robles, and Ceballos, we allow for a non-linear relationship between risk aversion and demand.

Whether households place more importance on absolute or relative risk is an empirical question that has not yet been addressed in the context of index insurance. To determine which is more important, we include total herd size and ratio of income generated from livestock and livestock related activities. Total herd size provides an absolute measure of exposure to asset risk associated with IBLI insurable assets, while the ratio of income that is generated from livestock and livestock related activities approximates the relative income risk associated with livestock mortality.

Theory and empirical evidence are also ambiguous as to how wealth should affect demand for insurance when prices are actuarially unfavorable. Clarke (2011) shows that the relationship between wealth and demand is not monotonic for most reasonable utility functions in such environments. Empirical studies offer contradictory evidence, finding that demand increases (e.g., Cole et al. 2013; Mobarak & Rosenzweig 2012) or decreases (e.g., McIntosh, Sarris, & Papadopoulos 2013) in variables associated with wealth. The literature on poverty traps, as has been demonstrated by multiple studies of east African pastoralists (Lybbert et al. 2004, Barrett et al. 2006, Santos and Barrett 2011), indicates that demand may be non-linear in wealth, changing dramatically across certain asset thresholds as households try to avoid or to break free of a low asset dynamic equilibrium (Chantarat et al. 2009; Janzen, Carter & Ikegami 2012; Lybbert, Just, & Barrett 2013). We summarize household wealth with an asset index generated through factor analysis of an extensive list of household construction materials, productive assets excluding livestock, and other durables (Appendix C).

Lack of liquidity is often found to constrain demand. Mobarak and Rosenzweig (2012) found that lack of cash was the primary reason given by Indian farmers for not purchasing an available index insurance product. Although liquidity is likely correlated with wealth, it can constrain demand at any wealth level (Cole et al. 2013). In order to capture liquidity, we calculate the sum of cash savings on hand or placed within any of several formal and informal savings arrangements. A household's savings are liquid and provide a lower band estimate of access to liquid capital. Descriptive statistics show that those households with savings have substantial amounts but that most households (74%) have no savings. Rather than use the continuous but highly skewed estimation of total savings, we use a dummy variable that is equal to one if the household has savings sufficient to purchase IBLI insurance for ten TLUs (≥8,250Ksh or ≥4,875 in the upper and lower contract regions, respectively). We also include an estimate of monthly income composed of earnings and the value of in-kind production.

The Hunger Safety Net Program (HSNP), an unconditional cash transfer program, launched in the Marsabit region in 2009, just before IBLI began. HSNP provides transfers every two months to eligible households for at least two years. The size of bi-monthly household transfers increased from 2,150Ksh in 2009 (about USD25) to 3,000Ksh in 2011 and then increased again in 2012 to 3,500Ksh in order to help households cope with a severe drought. 3,500Ksh could have purchased insurance for about 7 cattle in the lower Marsabit region at that time. There was no retargeting of or graduation from HSNP, which could have led to perverse incentives not to purchase IBLI if insurance has a beneficial impact on wealth. Although HSNP participation was not random within communities, we are able to cleanly identify the impact of transfers on demand by controlling for the known and corroborated household selection criteria and HSNP community selection.[56]

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[56] For more details on the HSNP program logistics go to http://www.hsnp.or.ke/ while analysis of impacts can be found in Hurrell & Sabates-Wheeler (2013) and Jensen, Mude and Barrett (2014).

Access to informal insurance schemes can be an important factor in demand for formal insurance. Mobarak and Rosenzweig (2012) show that informal risk pools that insure against idiosyncratic shocks complement index insurance with basis risk while informal schemes that protect against covariate shocks act as a substitute. In the pastoral societies of northern Kenya, informal risk sharing through livestock transfers and informal credit appears to be modest at best (Lybbert et al. 2004; Santos & Barrett 2011). Although there does seem to be a relationship between providing and receiving livestock transfers among Kenyan herders, those transfers are not timed so as to reduce the impact of shocks or to protect assets (McPeak 2006). But, because informal risk sharing is extremely relevant to this work and has empirically been found to impact demand for index insurance in India (Mobarak & Rosenzweig 2012), we include the number of informal groups that the household participates in as a coarse indicator of potential access to risk pooling.[57]

Table 6 describes how each of the variables is constructed and Table 7 provides summary statistics, distinguishing between those households who never purchased IBLI over the four sales windows and those who purchased at least once. Differences in unconditional means between the two groups show that IBLI purchasers have lower dependency ratios, face somewhat less livestock mortality risk, are less likely to be extremely risk averse, and more likely to have received a discount coupon in at least one of the sales windows. But, the two groups seem to be mostly similar as only the differences in dependency ratio, exogenous coupon receipt (and therefore in effective IBLI price) are statistically significant at the 5% level.

It is important to note that analysis of demand is performed seasonally while the survey data were collected annually. Although seasonal data were collected for many variables, some variables were collected for only

[57] Although ethnic group is also likely to be important in determining access to informal insurance, collinearity between ethnicity and location makes that aspect difficult to examine while also examining other variables that are correlated with location, such as the expected subsidy level and HSNP participation.

one reference point annually. In those cases, the annual values collected in October/November are used to represent household characteristics during the March-September LRLD insurance season and the current October-February SRSD season. In addition, many of the variables are lagged during analysis in order to avoid capturing changes due to paying the premium or due to behavior responses to having IBLI coverage. When estimating an average or distribution parameter (e.g., variance, covariance) all eight seasonal observations are used to estimate a single statistic, which is then treated as a constant over all periods. The temporal nature of the data used to construct each variable and which variables are lagged are described in greater detail in Table 6.

Finally, the IBLI contracts provide coverage for 12 months following the sales window in which they were purchased. If there had been sales windows before each semi-annual rainy season, it would be common for households to enter sales windows with existing coverage for the following season from the preceding season. They would then be making a decision whether to increase coverage by purchasing more or to maintain current coverage by purchasing nothing this period. Logistical problems faced by the insurer did not allow for consistent sales twice a year, but the survey does capture two consecutive sales seasons during which IBLI policies were sold. We expect that existing coverage still in force could impact purchase decisions and so control for existing coverage in that period.[58]

## Econometric strategy

We seek to identify the factors that influence demand for IBLI. Insurance demand is best modeled as a two stage selection process. Propensity to purchase is first determined as the household decides whether or not

[58] We use a dummy variable to indicate existing coverage. If households with existing coverage reduced purchases due to their existing coverage, a continuous variable might be more appropriate. That does not seem to be the case. Households with existing coverage are much more likely to purchase additional insurance than those without it (difference = 13.6%, t-statistic=4.265) but existing coverage does not impact level of purchase conditional on purchasing (difference = 0.22, t-statistic=0.387).

to buy IBLI. Those households who choose to purchase then decide how much to buy. Let $h_{it}^*$ and $y_{it}^*$ be latent variables that describe the categorical desire to purchase insurance and the continuous, optimal level of purchase, respectively. If $h_{it}^* > 0$ we observe the positive level of purchase $y_{it} = y_{it}^*$ , and if $h_{it}^* \leq 0$, we observe $y_{it} = 0$. We write the process as a function of time invariant individual characteristics $(c_i, d_i)$ including a constant term, time varying individual and division characteristics $(x_{it}, z_{it})$, and error terms $(u_{it}, v_{it})$ as follows.

(5)
$$y_{it}^* = c_i'\eta + x_{it}'\beta + u_{it}$$
$$h_{it}^* = d_i'\eta + z_{it}'\gamma + v_{it}$$
$$y_{it} = \begin{Bmatrix} 0 & if\ h_{it}^* \leq 0 \\ c_i'\eta + x_{it}'\beta + u_{it} & if\ h_{it}^* > 0 \end{Bmatrix}$$

If the same process is used to determine the desire to purchase insurance and the level of purchase, then $y_{it}^* \equiv h_{it}^*$ and the model reduces to Tobin's (1958) model for censored data. In the case of IBLI (and for many other cases) there is reason to believe that the two processes may differ. For example, the probability of purchasing any IBLI coverage is likely correlated with the distance that the purchaser must travel to make the purchase. There is little reason to think that the same distance variable would affect the level of purchase. If demand is a two stage process but the two decisions are independent (conditional on observed covariates), each stage can be estimated separately and consistently using a double hurdle model (Cragg 1971).

In this context, the two decisions most likely fall somewhere between Tobin's assumption that they are identical and Cragg's assumption that they are independent. That is, $u_{it}$ and $v_{it}$are not identical but they are correlated so that both the single model and independent models result in biased estimates of $\beta$. Heckman (1979) suggests that such bias is due to a missing variable that accounts for selection. To control for selection, Heckman proposed including the ratio of the predicted likelihood of selection to the cumulative probability of selection (the inverse Mills ratio). The inverse Mills ratio is estimated by first using a probit model to estimate $\Pr(s_{it} = 1 | d_{i,} z_{it}) = \Phi(d_{i,} z_{it}, \eta, \gamma)$, where $s_{it} = \begin{Bmatrix} 0 & if\ h_{it}^* \leq 0 \\ 1 & if\ h_{it}^* > 0 \end{Bmatrix}$. The estimates are then used to calculate the inverse Mills ratio $\hat{\lambda}_{it} = \frac{\phi(d_{i,} z_{it}, \hat{\eta}, \hat{\gamma})}{\Phi(d_{i,} z_{it}, \hat{\eta}, \hat{\gamma})}$, where $\phi(d_{i,} z_{it}, \hat{\eta}, \hat{\gamma})$ is the normal density.

Accounting for unobserved household level fixed effects is then a matter of applying panel data estimation methods to Heckman's framework. If intercepts among observations are common ($c_i = c, d_i = d$), pooled models suffice. Random effects probit/linear models are consistent as long as the intercepts are uncorrelated with the covariates ($x_{ti}, z_{ti}$). But, if the individual fixed effects are correlated with explanatory variables then the random effects estimates are inconsistent. For short panels, the standard fixed effects approaches suffer from the incidental parameters problem when applied to probit models.[59] But, if the data generating process is best described by the fixed effects model, pooled and random effects models will also be biased. Greene (2004) compares the magnitude of the bias introduced by estimating pooled, random effects, and fixed effects probit parameters for data generated by a probit process with fixed effects. At T=3 and T=5, Greene finds the random effects estimates are the most biased, and that the bias associated with the pooled and fixed effects models are similar in magnitude. In addition, standard errors are likely to be underestimated in the fixed effect model. We include pooled estimates in this analysis, acknowledging their likely bias but appealing to Greene's (2004) result that these are likely least bad estimates.

As an alternative, we also follow a procedure developed by Wooldridge (1995), which builds off of earlier work by Mundlak (1978) and Chamberlain (1980), to allow for correlation between the fixed effects and a

[59] Because the probit model is non-linear the parameters must be estimated using within household observations, of which we have a maximum of four.

subset of within-household mean characteristics ($\bar{x}_i^{FE}$) but assume independence conditional on the mean. In addition the errors are assumed to be distributed normally.

(6)
$$c_i = \bar{x}_i^{FE\prime}\gamma_1 + e_{it}^c, e_{it}^c|\bar{x}_i^{FE} \sim N(0, \sigma_e^2)$$
$$d_i = \bar{x}_i^{FE\prime}\delta_1 + e_{it}^d, e_{it}^d|\bar{x}_i^{FE} \sim N(0, \sigma_e^2)$$
$$\bar{x}_i^{FE} = \frac{1}{T}\sum_T x_{it}^{FE}, x_{it}^{FE} \subseteq x_{it}, z_{it}$$

As with the Heckman selection process described above, a probit model is used estimate the inverse Mills ratio, but in this case the estimate is a function on household average characteristics and period specific characteristics $\hat{\lambda}_{it} = \frac{\phi(\bar{x}_i^{FE'}, z_{it}, \hat{\delta}_1, \hat{\eta}, \hat{\gamma})}{\Phi(\bar{x}_i^{FE'}, z_{it}, \hat{\delta}_1, \hat{\eta}, \hat{\gamma})}$. In order to add more flexibility, and thus accuracy, to the first stage estimations, the probit model is estimated separately for each period.

Within household mean characteristics are estimated using all eight seasonal observations while $s_{it}$ and $y_{it}$ are only estimated during the four seasons in which there were sales. To make interpreting the impact of household characteristics on demand easier, any variable that includes its mean in the regression is demeaned.

We report the pooled and the conditionally independent fixed effects estimates, while relying primarily on the latter as the preferred estimates. If the data generating process does include unobserved individual effects that are correlated with our outcome variables and the covariates, our pooled estimates are likely to be biased but perform better than either random or fixed effects models (Greene 2004). The conditionally independent fixed effects should generate estimates that are at the very least, less biased than those from the pooled model.

Both models are estimated using maximum likelihood. Although effective (discounted) price is included in both selection and demand equations, a dummy variable indicating that the household randomly received a discount coupon is included in the selection equation but is excluded from the demand equation. The discount coupon serves merely as a reminder of the product availability and thus should affect the dichotomous purchase decision but have no effect on the continuous choice of insurance coverage conditional on purchase once we control for the effective discounted price. Although there is no agreed upon exclusion test for selection models, we perform two exploratory tests that support the exclusionary restriction on the coupon dummy variable in the demand equation, as reported in Appendix D.

## Results and Discussion

Wooldridge (1995) describes a test for selection that assumes conditionally independent fixed effects in the selection stage but relaxes that assumption in the outcome stage. That test rejects the null hypothesis of an independent second stage (*F-stat*=48.97, *p-value*=0.00). Thus, demand for IBLI can only be understood by first examining the factors that determine who purchases IBLI and then what drives level of purchase conditional on purchasing. In the following discussion we focus on the estimates generated from the conditional fixed effects model while also reporting the pooled estimates. The average marginal effects estimates are provided in tables 8 and 10 while the regression coefficient estimates can be found in Appendix E.[60]

### *Determinants of IBLI uptake*

Male headed households have a greater propensity to purchase IBLI (Table 8). The relationship between wealth, access to liquidity, investments in livestock, and uptake are predictably complicated. Herd size and

[60] The second stage of the conditional fixed effects model is estimated using inverse Mills ratios generated by estimating the first stage probit model separately for each period. In tables 8 and E.1, we present the average coefficient estimates generated by pooling the four periods, including both time specific and household average characteristics.

HSNP transfers are positively related to IBLI purchase while asset wealth and cash savings are negatively related to purchases. Although these estimates may seem superficially contradictory, in the context of a new technology in a pastoral region they strike us as intuitive. Households with larger herds have the greater potential absolute gains from the IBLI product. Large herds also require mobility to maintain access to forage (Lybbert et al. 2004) and many of the larger assets included in the asset index (e.g., TV, tractor, plow) and cash savings are likely to be less appropriate for mobile, livestock-dependent households for whom IBLI should be most valuable.

There is weak evidence of temporal adverse selection and strong evidence of spatial adverse selection. Households in divisions with lower variation in losses and less idiosyncratic risk (as captured by greater average correlation between losses and the index) are more likely to purchase IBLI. The negative relationship between idiosyncratic risk and uptake is consistent with the predictions made by our analytic model. The fact that greater variation in livestock losses is associated with reduced uptake requires a closer look at the data. One likely explanation is that there is greater idiosyncratic risk (and thus basis risk) in divisions with more variation in losses. We test for a positive correlation between division average variance in livestock mortality rate and division average idiosyncratic risk, finding that the correlation is positive and significant (rho=0.98, p-value=0.004, N=4).

Observed design error has a significant and negative AME on uptake. Although the estimated AME of price is statistically insignificant, the coefficient estimates (Table E.1) show that the price coefficient and the interaction between price and observed design error are important. Examining the estimated AMEs of design error across a range of observed IBLI prices reveals that observed design error reduces the likelihood of purchasing IBLI by about 1.5% when prices are one standard deviation above the mean, but that at lower prices the impact of observed design error becomes insignificant (Table 9). The same test for changes to price response at various levels of observed design error design shows that design error is not a significant factor in price response of uptake (Table 9).

Households with consistently high participation in social groups have a greater propensity to purchase IBLI (Table 8). Although participating in social groups could be endogenous to purchasing IBLI, we find that a household's average participation (including 3 seasons before the first sales season) is has a positive and significant impact on uptake. Plausible explanations for the positive relationship between social group participation and purchasing IBLI include the complementarities between index insurance and informal idiosyncratic risk pooling described by Mobarak and Rosenzweig (2012) and learning through social networks (Cai, de Janvry & Sadoulet 2011).

Randomized exposure to the IBLI educational game allows us to look more closely at the impact of learning. Here we see that increased IBLI knowledge associated with participating in the game has no discernible impact on the decision to purchase IBLI (Table 9), although we know it does have a strong impact on understanding of the IBLI product (Table 4). In that case, it seems less likely that the pathway by which participation in social groups impacts demand is through increased understanding of the product and the argument that social group linkages stimulate IBLI uptake due to complementarities with informal insurance is stronger.

The discount coupon, which is excluded in the second stage, has an AME of about 20% on the likelihood of purchasing insurance and is statistically significant at the one percent level. Quite apart from the price effect of the discount coupon, it seems to serve a useful role as a visible reminder to households of the availability of insurance.

***Quantity of Insurance Purchased***

The continuous IBLI purchase decision reveals some of the same patterns evident in the decision to purchase (Table 10). Larger herds are again associated with increased demand.[61] But, among those purchasing, demand increases with greater asset wealth, more savings, and income diversification into non-livestock related activities (nearly all of which is generated earnings). Jointly, these results provide strong evidence that demand is liquidity constrained among those seeking to purchase IBLI.[62] Referring back to our model of household demand for insurance, we could not analytically sign many of the relationships between characteristics and demand because of the ambiguity of the wealth effect on demand. Empirically we also find mixed responses, such as asset wealth reducing the likelihood of uptake but increasing coverage levels conditional on uptake, while livestock wealth is associated with increases in both uptake and conditional coverage levels.

There is evidence of both inter-temporal and spatial adverse selection in IBLI purchases conditional on positive demand. Households expecting good rangeland conditions but who still bought insurance, purchased about 8.8% less coverage than those expecting poor conditions. The coefficient estimate for Pre-Czndvi (a division level proxy for rangeland conditions at the time of sale) is also negative but just insignificant at the 10% level (p-value=0.109). Division level risk has a positive impact on level of purchase so that households in divisions with high average risk are less likely to purchase but buy more coverage, conditional on purchasing. In addition, those divisions with lower average livestock mortality rates purchase less.

The correlation between individual and covariate losses plays a role in determining level of demand, although its impact is somewhat obscured by interactions (Table E.2). Separating purchasers by game play,

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[61] The AME of herd size is positive but less than one, revealing that households with larger herds do insure more animals but they are insuring a smaller portion of their total herd.

[62] All household income was derived from livestock in about 53% of the household observations during sales season. During the same periods, 47% of the households that purchased insurance generated all of their income from livestock in the period that they purchased. Non-livestock income sources captured in the survey are from sale of crops, salaried employment, pensions, casual labor, business, petty trading, gifts, and remittances.

the estimated AME of the correlation between an individual's losses and the covariate losses of their division is negative and significant for households who did not participate in the IBLI extension game but positive (p-value=0.109) for those who did play the game, weakly confirming our hypothesis on the interaction between understanding the IBLI product and the impact of basis risk on demand (Table 11). As discussed in Section 4, participation in the IBLI game was randomized and has a large and significant impact on understanding of the IBLI product (Table 4). Here we see that purchase levels are higher among those with greater covariate (insurable) risk and lower among those with less covariate risk among those who participated in the game, as our model predicts, although we cannot empirically identify how playing the extension game produces these differences. On the other hand, those households who did not participate in the educational game make purchase decisions oddly related to their covariate risk exposure; those facing little covariate risk purchased more than those with high covariate risk exposure.[63]

Price is a significant factor influencing demand conditional on uptake, but demand is rather price inelastic, with a point estimate of -0.34, lower than any of the other estimates we find in the literature. Examining the impact of observed design error on the price elasticity of demand, we find that the statistical relationship between increased premiums and purchase levels grows stronger at higher levels of observed design error (Table 11). But, there is no direct negative effect of design error on level of purchase even at high premium levels. Jensen, Barrett and Mude (2014) shed some light on why households may not have responded to design risk directly; in most cases design risk is minor when compared to idiosyncratic risk. Hence our findings that demand is much more closely linked with idiosyncratic risk indicators make perfect sense.

[63] Household level risk is accounted for in the risk variable so that this effect is not due to level of covariate risk picking up the effects of total risk. In addition, very few households ever purchase coverage for more animals than they hold so that this is unlikely to be the result of households (mistakenly) over-insuring to make up for uninsured idiosyncratic risk.

## Concluding Remarks

The above analysis provides strong empirical evidence that in addition to price and household demographic characteristics, adverse selection and basis risk play economically and statistically significant roles in determining demand. The point estimates from our analysis (Table E1 and E2) predict the changes in IBLI purchases over time rather well, showing a reduction in uptake after the first period and a small upturn in the final period (Figure 4 and Figure 5).

A Shapley's $R^2$ decomposition can shed some light on which factors contribute most to explaining variation in IBLI uptake and level of purchase. After grouping the covariates into several categories, we re-estimate the uptake and demand equations separately and decompose their goodness of fit measures using the user-written command *shapely2* (Juárez 2014), which builds off earlier work by Kolenikov (2000) and theory by Shapley (1953) and Shorrocks (2013).[64] The Shapley $R^2$ decompositions reported in Appendix F should be interpreted as the ratio of the model's goodness of fit ($R^2$ or Pseudo $R^2$) that can be attributed to the group of variables. For both uptake and level of demand, the total role of adverse selection and product related variables in explaining demand is similar but larger than that of household characteristics (demographics and financial), providing strong evidence that product design and the nature of the insured risk are at least as important as household demographic characteristics. The Shapley values indicate that the three variables associated with design risk and price are responsible for 18% of our goodness of fit measure for the uptake model, a considerable achievement considering that there are more than 25 other covariates and that the discount coupon accounts for nearly 37% of the model's fit. The role of design risk and price falls when examining level of purchase, where the importance of both spatial and temporal adverse selection increase to 16% in both cases. The importance of idiosyncratic risk to the fit of the model

[64] The variable categories are demographic, financial, intertemporal adverse selection, spatial adverse selection, idiosyncratic risk and knowledge, design risk and price, other, and the instrument variable.

is fairly low and consistent in both uptake (6.5%) and level of purchase (10.5%).

With the model estimates and Shapely values in mind, it is clear that both product and household characteristics play an important role in determining demand for index insurance. Insurance products can do little to change household characteristics; but it may be possible to lessen adverse selection and idiosyncratic risk through improved contract design. For example, IBLI no longer aggregates index divisions into premium regions, removing one source of adverse selection. Adjusting premium rates dynamically to account for initial season conditions is an additional step that could be taken to reduce adverse selection. Idiosyncratic risk limits the potential impact of even a perfect index product, but is in part a construct of the index division, which could be adjusted to increase the importance of covariate risk. And finally, reducing design risk is likely to be relatively simple if household-level data is collected and used to improve the performance of the index.

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## Figures

**Figure 1**. Survey design, participation in IBLI game and HSNP target sites

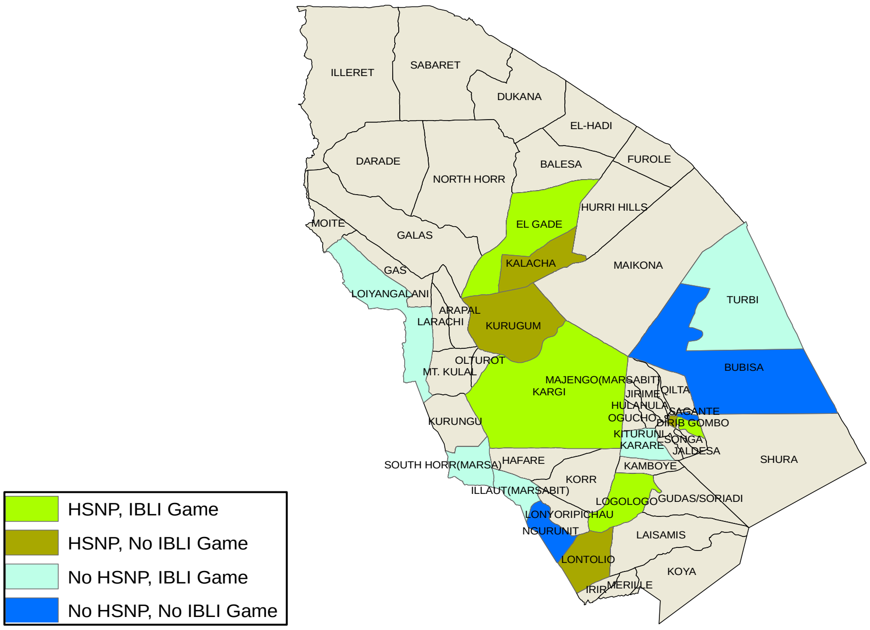


**Figure 2.** IBLI purchasing behavior during each sales window

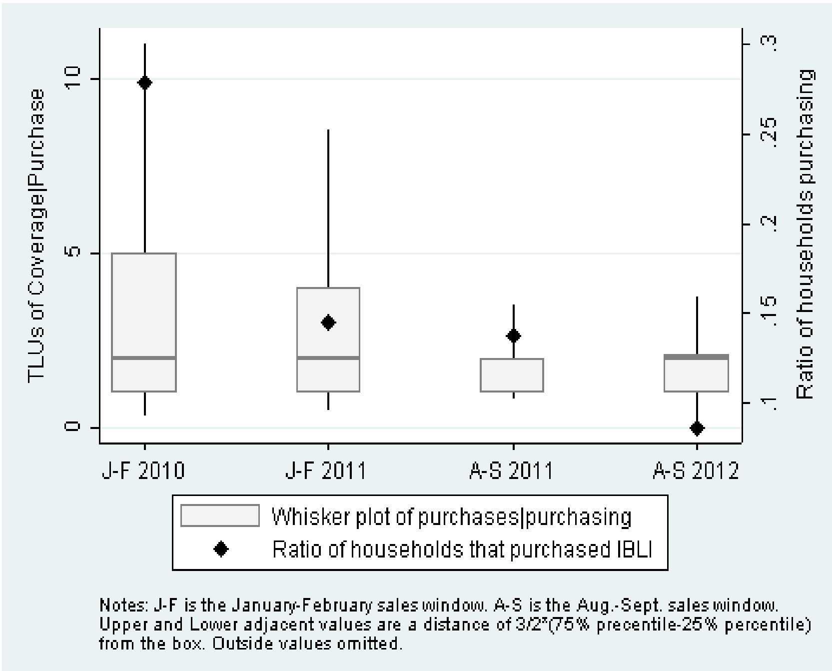



**Figure 3.** Histograms of the correlation between individual and covariate livestock mortality rates

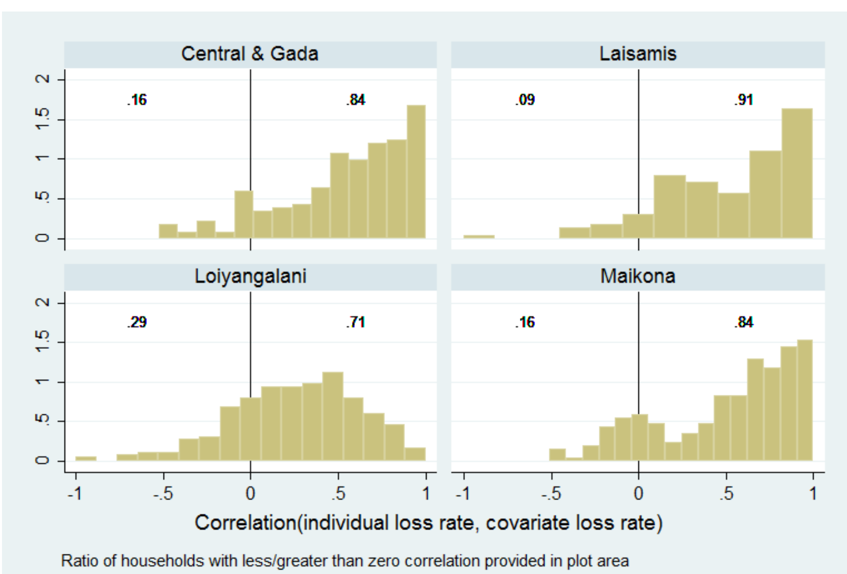


**Figure 4.** Unconditional observed and predicted (Conditional FE) likelihood of purchasing IBLI

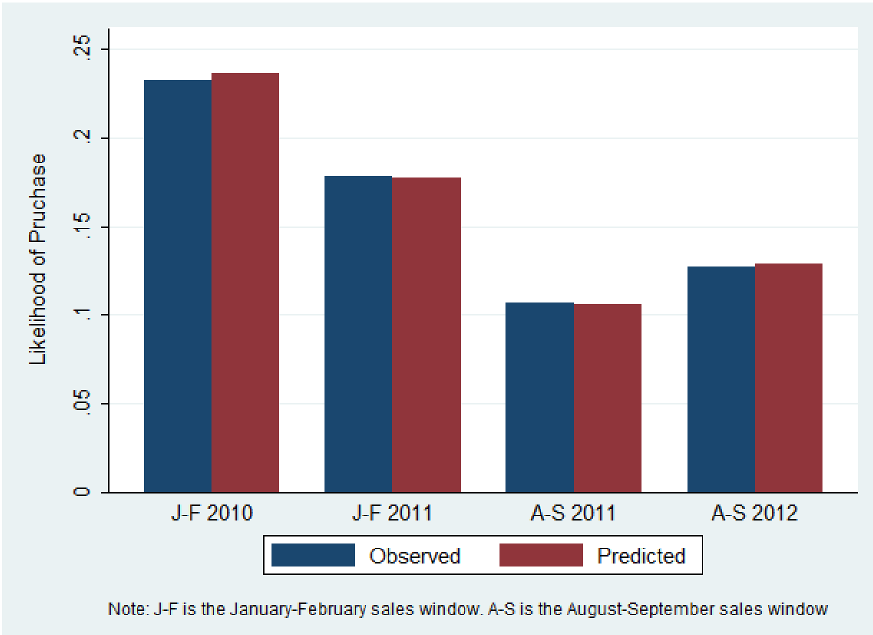
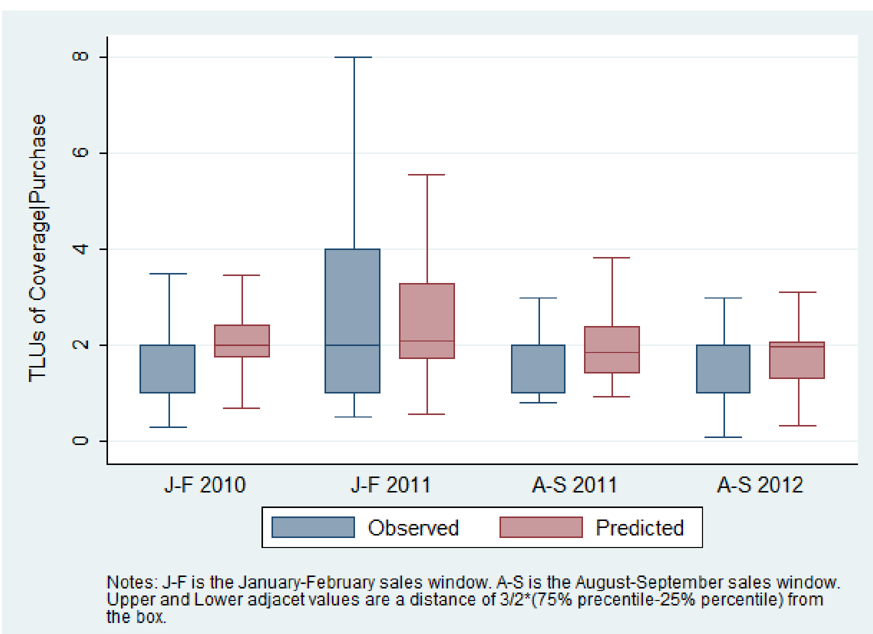



**Figure 5.** Observed and predicted (Conditional FE) level of purchases, conditional on being a purchaser



## Tables

**Table 1**. Representation of demand for IBLI in the survey sample

| Survey[#] | Sales Window | IBLI Coverage Period | | Total Contracts Sold | IBLI survey households: Did Not Purchase | IBLI survey households: Purchased |
|---|---|---|---|---|---|---|
| R1 (2009) | - | - | | - | - | - |
| | - | - | | - | - | - |
| R2 (2010) | J-F 2010 | LRLD10/SRSD10 | (N) | 1,974 | 664 | 256 |
| | | | (Mean) [&] | 3.0 | - | (3.76) |
| | - | - | (N) | - | - | - |
| | | | (Mean) [&] | - | - | - |
| R3 (2011) | J-f 2011 | LRLD11/SRSD11 | (N) | 595 | 790 | 134 |
| | | | (Mean) [&] | (2.1) | - | (3.07) |
| | A-S 2011 | SRSD11/LRLD12 | (N) | 509 | 797 | 127 |
| | | | (Mean) [&] | (1.6) | - | (2.39) |
| R4 (2012) | - | - | (N) | - | - | - |
| | | | (Mean) [&] | - | - | - |
| | A-S 2012 | SRSD12/LRLD13 | (N) | 216 | 844 | 80 |
| | | | (Mean) [&] | (1.9) | - | (2.68) |

LRLD and SRSD refer to the long rain/long dry and short rain/short dry season respectively. There were no sales during the Aug/Sept 2010 and Jan/Feb 2011 sales periods due to supply channel failures. Jan/Feb 2010, Jan/Feb 2011 & Aug/Sept 2011 were sold under UAP. Aug/Sept 2012 was sold under APA. [#]Surveys were collected during October and November of each year. [&]Mean is the mean coverage purchased in TLUs, conditional on purchasing IBLI.

**Table 2. Household IBLI purchase patterns, by sales window**

| Sales window | New[1] | Replacement[2] | Augmenting[3] | Holding[4] | Reenter[5] | Lapsed[6] | Total[7] |
|---|---|---|---|---|---|---|---|
| J-F 2010 | 233 | 0 | 0 | 0 | 0 | 0 | 233 |
| J-F 2011 | 65 | 62 | 0 | 0 | 0 | 171 | 298 |
| A-S 2011 | 65 | 0 | 31 | 96 | 22 | 149 | 363 |
| A-S 2012 | 19 | 25 | 0 | 0 | 33 | 305 | 382 |

We use the balanced panel of 832 households in this table to track household purchase behavior over time. Therefore, columns do not sum to the totals reported in Table 1. [1]First time purchasers. [2]Replaced a policy about to expire. [3]Purchased additional coverage that overlapped with existing coverage. [4]No purchase but had existing coverage. [5]Let policy lapse for at least one season but purchased this season. [6]Past policies have lapsed and did not purchased additional coverage. [7]Total number of households that have purchased to date.

**Table 3.** The average observed design error in each division at each sales period

| Sales Seasons | Design Risk Observations | Observed Average Estimated Design Error | | | |
|---|---|---|---|---|---|
| | | Central/ Gadamoji | Laisamis | Loiyangalani | Maikona |
| J-F 2010 | - | 0 | 0 | 0 | 0 |
| J-F 2010 | LRLD 2010 | 0.052 | 0.111 | 0.103 | 0.041 |
| A-S 2011 | LRLD 2010, SRSD 2010 | 0.064 | 0.098 | 0.115 | 0.056 |
| A-S 2012 | LRLD 2010, SRSD 2010, LRLD 2011, SRSD11 | 0.020 | 0.011 | 0.079 | 0.027 |

LRLD and SRSD refer to the long rain/long dry and short rain/short dry season respectively. The observed average estimated design error is the mean difference between covariate loss rate and the predicted loss rate (index) during previous seasons with potential IBLI coverage.

**Table 4.** The impact of the randomized extension game on understanding of the IBLI contracts

| | Not game participant | | Game participant | | | |
|---|---|---|---|---|---|---|
| IBLI Knowledge: | Mean | Std. Err. | Mean | Std. Err. | Difference | t-test |
| Full Sample | 1.74 | 0.802 | 2.31 | 0.122 | 0.56 | 3.81*** |
| Never Purchase | 1.53 | 0.107 | 2.14 | 0.165 | 0.61 | 3.09*** |

The game was played in January 2010. The scores above reflect the number of survey questions, which tested household understanding of IBLI contract details, correctly answered. Significance is indicated by: *** p<0.01, ** p<0.05, * p<0.1

**Table 5.** Rangeland conditions during each sales window as predictors of final index value

| Variable | Index | Index | Index |
|---|---|---|---|
| Pre-Czndvi | -0.0067** | | -0.0059*** |
| | (0.0026) | | [0.0001] |
| Expected rangeland condition[1]: | | | |
| Good | | -0.0773*** | -0.0519*** |
| | | [0.0049] | [0.0046] |
| Normal | | -0.0512*** | -0.0411*** |
| | | [0.0049] | [0.0046] |
| District fixed effects: | | | |
| Laisamis | -0.0399 | -0.0061 | -0.0316*** |
| | (0.0698) | [0.0064] | [0.0016] |
| Loiyangalani | -0.0473 | -0.0397*** | -0.0439*** |
| | (0.0692) | [0.0019] | [0.0014] |
| Maikona | -0.0115 | -0.0032 | -0.0133*** |
| | (0.0694) | [0.0020] | [0.0015] |
| Constant | 0.1009* | 0.1784*** | 0.1403*** |
| | (0.0502) | [0.0038] | [0.0037] |
| | | | |
| Observations | 16 | 2,713 | 2,690 |
| R-squared | 0.3946 | 0.1179 | 0.3842 |

Four seasons' data for four divisions with Central & Gadamoji division dummy omitted. [1] The expected conditions variables are the division-season average of a set of dummy variables for expected conditions are: good, normal, or bad. *Expected conditions: Bad* is the omitted category. Standard errors in parentheses. Robust and clustered standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

**Table 6.** Description of key variables

| Variable | Data Frequency | Description |
|---|---|---|
| Male | Annual | Sex of the head of household (1=male). |
| Age of head | Annual | Age of the head of household (years). |
| Education | Annual | Maximum education level achieved within the household (years). |
| Risk aversion: neutral | Constant | Following Binswanger (1980), households were allowed to choose from a menu of real gambles in which level of risk and expected outcome were positively correlated. Each household participated in the experiment once during their first survey round. Households are then placed into a risk aversion category according to the lottery that they choose. The categories are risk neutral, moderately risk averse, and extremely risk averse. |
| Risk aversion: moderate | Constant | |
| Risk aversion: extreme | Constant | |
| Dependency Ratio | Annual | Ratio of members that are younger than 15 years, older than 55 years, disabled, or clinically ill. |
| Social groups | Annual | A count of the number of informal groups in which the household participates. This variable is lagged by one period in the analysis. |
| Asset index | Annual | The asset index is generated by a factor analysis performed on more than 30 variables capturing asset ownership from the following categories: productive assets, household construction materials, household facilities, cooking and lighting fuels, and consumer durables. This variable is lagged by one period in the analysis. |
| Ln income | Seasonal | Ln(1+ average monthly income) where income is the sum of the value of earnings, milk production, livestock slaughter, and livestock sales. Earnings include earnings from sale of crops, salaried employment, pensions, casual labor, business, petty trading, gifts, and remittances, expressed in Kenyan shillings (Ksh). This variable is lagged by one period in the analysis. |
| Ratio livestock income | Seasonal | Ratio of income that is generated through milk production, livestock slaughter or livestock sales. This variable is lagged by one period in the analysis. |
| Herd size | Seasonal | Average herd size during the sales window (1 TLU=0.7 camels=1 cattle=10 sheep=10 goats). This variable is lagged by one period in the analysis. |
| Livestock mortality rate | Seasonal | Seasonal livestock mortality rate is calculated by dividing total losses within a season by the total herd owned within that season. Total herd owned is the sum of beginning herd size and all additions to the herd during the season. This variable is lagged by one period in the analysis. |
| Risk | Constant | Within household variance in livestock mortality rate |
| Savings | Annual | A dummy variable that is equal to one if the household has cash savings sufficient to purchase IBLI insurance for ten TLUs. Savings are estimated by summing the total monies held at home, in merry-go-round groups, in micro-finance institutions, in savings and credit cooperatives, in bank accounts, with traders or shops, and in M-Pesa (a mobile-based micro-finance institution) accounts. This variable is lagged by one period in the analysis. |
| HSNP | Seasonal | Participation in HSNP (1=participant). This variable is lagged by one period in the analysis. |
| HSNP community | Seasonal | Community is an HSNP target community (1=target community). |
| Expected rangeland: Good/Normal/Poor | Annual | A set of three dummy variables reflecting that the respondent's prediction of coming season's rangeland conditions were: much above normal or above normal (Good=1), normal (Normal=1), or somewhat below normal or much below normal (Poor=1). |
| Ln(effective price) | Seasonal | Log of the price for one TLU of coverage after coupon discounts (ln(Ksh)). |
| Design Error | Seasonal | The mean observed design error (%). |
| Correlation(M,CL) | Constant | The correlation between individual and covariate seasonal livestock mortality rates. For households with no variation in livestock mortality rate, this is set to zero. |
| IBLI game | Constant | Household participated in the IBLI educational game in 2010 (1=participant). |
| IBLI coverage | Seasonal | Household has existing IBLI coverage (1=true). |
| Coupon | Seasonal | Household received a discount coupon (1=true). |
| Pre-Czndvi | Seasonal | Preceding season's cumulative standardized normalized difference vegetation index. |
| Division Livestock Mortality | Division Constant | The eight-period average loss rate of all households within each division. |
| Division Risk | Division Constant | The within-household variance in loss rate averaged across all households in each division. |
| Division Correlation | Division Constant | The within-household correlation between individual loss rate and covariate loss rate averaged across all households in each division. |

**Table 7.** Summary statistics

| Variable | Never Purchase (N=450) Mean | Std. Err. | Did Purchase (N=382) Mean | Std. Err. | Difference | t-stat |
|---|---|---|---|---|---|---|
| Gender | 0.54 | 0.05 | 0.63 | 0.06 | 0.09 | 1.25 |
| Age | 4.54 | 0.12 | 4.95 | 0.27 | 0.41 | 1.39 |
| Education | 3.52 | 0.31 | 4.02 | 0.53 | 0.50 | 0.83 |
| Risk aversion: | | | | | | |
| Neutral | 0.25 | 0.05 | 0.24 | 0.05 | -0.01 | -0.13 |
| Moderate | 0.43 | 0.05 | 0.56 | 0.07 | 0.13 | 1.49 |
| Extreme | 0.32 | 0.05 | 0.21 | 0.05 | -0.12 | -1.64 * |
| Dependency Ratio | 0.64 | 0.02 | 0.57 | 0.03 | -0.07 | -2.37 ** |
| Social Groups | 0.51 | 0.05 | 0.61 | 0.06 | 0.10 | 1.28 |
| Asset Index | 0.95 | 0.06 | 0.99 | 0.07 | 0.04 | 0.37 |
| Income | 7,787 | 625 | 7,938 | 711 | 151 | 0.16 |
| Ratio livestock income | 0.62 | 0.03 | 0.61 | 0.04 | -0.01 | -0.28 |
| Herd size | 1.30 | 0.12 | 1.14 | 0.12 | -0.16 | -0.93 |
| Livestock mortality rate | 0.16 | 0.01 | 0.13 | 0.01 | -0.03 | -2.83 *** |
| Savings | 0.07 | 0.02 | 0.08 | 0.02 | 0.01 | 0.32 |
| HSNP | 0.25 | 0.03 | 0.28 | 0.04 | 0.03 | 0.49 |
| HSNP Community | 0.79 | 0.03 | 0.73 | 0.04 | -0.06 | -1.17 |
| Expected rangeland conditions: | | | | | | |
| Good | 0.44 | 0.02 | 0.41 | 0.02 | -0.03 | -1.05 |
| Normal | 0.35 | 0.02 | 0.35 | 0.02 | 0.00 | 0.11 |
| Poor | 0.21 | 0.02 | 0.24 | 0.03 | 0.03 | 0.79 |
| Pre-Czndvi | 0.00 | 0.00 | 0.09 | 0.01 | 0.09 | 9.46 *** |
| IBLI coverage | -2.78 | 0.14 | -2.82 | 0.15 | -0.03 | -0.16 |
| Risk | 0.06 | 0.01 | 0.04 | 0.00 | -0.02 | -2.81 *** |
| Correlation(M, CL) | 0.43 | 0.03 | 0.47 | 0.04 | 0.04 | 0.76 |
| IBLI game | 0.24 | 0.04 | 0.21 | 0.04 | -0.03 | -0.64 |
| Ln(effective price) | 6.19 | 0.01 | 6.14 | 0.01 | -0.05 | -2.69 *** |
| Design Error | 2.17 | 0.07 | 2.28 | 0.08 | 0.11 | 1.03 |
| Coupon | 0.54 | 0.04 | 0.64 | 0.03 | 0.09 | 2.02 ** |

This table only includes the 832 balanced panel households in order to correctly categorize the “Never Purchase” households and maintain consistency in the periods and shocks captured in the summary statistics. Within-household average data are used in this table. The data used in this table are within-household average data. *** p<0.01, ** p<0.05, * p<0.1

**Table 8.** Average marginal effects (AME) on IBLI uptake, from probit

| | **Pooled** | | **Conditional FE** | |
|---|---|---|---|---|
| VARIABLES | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Household Period-Specific Characteristics: | | | | |
| Male | 0.0434* | (0.0258) | 0.0439* | (0.0248) |
| Dependency Ratio | -0.1157** | (0.0581) | 0.0019 | (0.0952) |
| Social Groups $^{L}$ | 0.0166 | (0.0117) | 0.0014 | (0.0132) |
| Asset Index $^{L}$ | -0.0768** | (0.0340) | -0.0669** | (0.0288) |
| Ln(income) $^{L}$ | -0.0057 | (0.0094) | -0.0085 | (0.0066) |
| Ratio income livestock $^{L}$ | -0.0628* | (0.0340) | 0.0031 | (0.0339) |
| TLU $^{L}$ | 0.0097 | (0.0134) | 0.0244** | (0.0121) |
| Livestock Mortality Rate $^{L}$ | 0.0000 | (0.0445) | 0.0420 | (0.0451) |
| Savings (10TLU) $^{L}$ | 0.0031 | (0.0549) | -0.0648* | (0.0393) |
| HSNP $^{L}$ | 0.0636** | (0.0265) | 0.0617** | (0.0243) |
| *Household Average Characteristics:* | | | | |
| Dependency Ratio | | | -0.1632*** | (0.0612) |
| Social Groups | | | 0.0441** | (0.0207) |
| Asset Index | | | -0.0126 | (0.0261) |
| Ln(income) | | | -0.0015 | (0.0102) |
| Ratio income livestock | | | -0.0385 | (0.0515) |
| TLU | | | -0.0010 | (0.0080) |
| Livestock Mortality Rate | | | -0.1529 | (0.2389) |
| Savings (10TLU) | | | -0.0927 | (0.0777) |
| Expected Rangelands: Good$^{\#}$ | | | -0.0497 | (0.0674) |
| Expected Rangelands: Normal$^{\#}$ | | | -0.0256 | (0.0799) |
| *Prospective Adverse Selection:* | | | | |
| Expected conditions: Good$^{\#}$ | -0.0589** | (0.0265) | -0.0660 | (0.0638) |
| Expected conditions: Normal$^{\#}$ | -0.0166 | (0.0271) | 0.0365 | (0.0283) |
| Pre-CZNDVI | -0.0001 | (0.0017) | 0.0042 | (0.0266) |
| Division Livestock Mortality | 0.0567** | (0.0258) | -0.0176 | (0.0529) |
| Division Risk | -0.0533* | (0.0292) | -0.0067** | (0.0029) |
| Division Correlation | 0.2721 | (0.2121) | 0.1924*** | (0.0379) |
| *Product Related Characteristics :* | | | | |
| Existing IBLI Coverage | -0.0546 | (0.0572) | -0.0660 | (0.0638) |
| Risk | -0.6974*** | (0.2581) | -0.3117 | (0.4008) |
| Correlation | 0.0346 | (0.0286) | 0.0365 | (0.0283) |
| Extension Game | -0.0043 | (0.0273) | 0.0042 | (0.0266) |
| Ln(price) | -0.0065 | (0.0598) | -0.0176 | (0.0529) |
| Observed Design Error (ODE) | -0.0063** | (0.0029) | -0.0067** | (0.0029) |
| Coupon Dummy | 0.2033*** | (0.0450) | 0.1924*** | (0.0379) |
| | | | | |
| Observations | 3,407 | | 3,407 | |
| F-statistic | 5.01 | | 5.12 | |
| P-value (model) | 0.00 | | 0.00 | |

Additional covariates not listed above include age, age$^2$, average age (for the Conditional FE model), education, level of risk aversion, HSNP Village and a constant. $^{L}$ Variable is lagged one period. $^{\#}$Omitted variable is E*xpected conditions: poor*. Robust and clustered standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

**Table 9.** AME of the interacted variables on the likelihood of purchasing IBLI

| | AME | Std. Err. | t | P>t | Confidence Interval | |
|---|---|---|---|---|---|---|
| **Price =** | **Observed Design Error** | | | | | |
| Mean-1 SD | -0.0026 | 0.0033 | -0.80 | 0.424 | -0.009 | 0.004 |
| Mean Price | -0.0092 | 0.0030 | -3.05 | 0.002 | -0.015 | -0.003 |
| Mean +1SD | -0.0152 | 0.0048 | -3.14 | 0.002 | -0.025 | -0.006 |
| | | | | | | |
| **Observed Design Error=** | **Price** | | | | | |
| Mean-1 SD | 0.0841 | 0.0663 | 1.27 | 0.205 | -0.053 | 0.187 |
| Mean ODE | -0.0122 | 0.0513 | -0.24 | 0.811 | -0.113 | 0.088 |
| Mean +1SD | -0.0973 | 0.0656 | -1.48 | 0.138 | -0.188 | 0.044 |
| | | | | | | |
| **Extension Game** | **Correlation(M,CL)** | | | | | |
| No | 0.0315 | 0.0307 | 1.03 | 0.305 | -0.029 | 0.092 |
| Yes | 0.0551 | 0.0607 | 0.91 | 0.364 | -0.064 | 0.174 |

**Table 10.** Average marginal effects (AME) on level of purchase, conditional on purchase

| | **Pooled** | | **Conditional FE** | |
|---|---|---|---|---|
| VARIABLES | Coefficient | Std. Err. | Coefficient | Std. Err. |
| *Household Period-Specific Characteristics:* | | | | |
| Male | 0.0949 | (0.0926) | 0.1309 | (0.0968) |
| Dependency Ratio | -0.2679 | (0.2649) | 0.4853 | (0.7027) |
| Social Groups [L] | 0.0295 | (0.0510) | -0.0206 | (0.0582) |
| Asset Index [L] | 0.0698 | (0.1057) | 0.2273** | (0.0989) |
| Ln(income) [L] | 0.0099 | (0.0375) | 0.0303 | (0.0263) |
| Ratio income livestock [L] | -0.4854*** | (0.1742) | -0.5312*** | (0.1773) |
| TLU [L] | 0.0909* | (0.0527) | 0.1421** | (0.0614) |
| Livestock Mortality Rate [L] | 0.2142 | (0.2598) | 0.0960 | (0.2071) |
| Savings (10TLU) [L] | 0.3334*** | (0.1230) | 0.4070** | (0.1796) |
| HSNP [L] | -0.0657 | (0.1010) | -0.2116* | (0.1176) |
| *Household Average Characteristics:* | | | | |
| Dependency Ratio | | | -0.5163* | (0.2736) |
| Social Groups | | | -0.0341 | (0.2445) |
| Asset Index | | | 0.1813** | (0.0872) |
| Ln(income) | | | 0.0198 | (0.0396) |
| Ratio income livestock | | | -0.1126 | (0.2159) |
| TLU | | | 0.0265 | (0.0576) |
| Livestock Mortality Rate | | | -0.3976 | (0.8158) |
| Savings (10TLU) | | | 0.1098 | (0.0830) |
| Expected Rangelands: Good[#] | | | -0.9911*** | (0.2847) |
| Expected Rangelands: Normal[#] | | | -0.8760*** | (0.2877) |
| *Prospective Adverse Selection:* | | | | |
| Expected conditions: Good[#] | -0.4403*** | (0.1005) | -0.2646** | (0.1086) |
| Expected conditions: Normal[#] | -0.3822*** | (0.1114) | -0.1584 | (0.0990) |
| Pre-CZNDVI | -0.0017 | (0.0047) | -0.0106 | (0.0066) |
| Division Livestock Mortality | -0.2592*** | (0.0926) | -0.1957** | (0.0840) |
| Division Risk | 0.2780*** | (0.1054) | 0.2451*** | (0.0942) |
| Division Correlation | -1.2820 | (0.7902) | -0.9065 | (0.7202) |
| *Product Related Characteristics :* | | | | |
| Existing IBLI Coverage | 0.0099 | (0.1794) | -0.0612 | (0.1961) |
| Risk | -1.2138 | (1.2112) | 0.9285 | (1.5273) |
| Correlation | -0.2420** | (0.1013) | -0.2555** | (0.1146) |
| Extension Game | 0.1030 | (0.0838) | 0.1102 | (0.0859) |
| Ln(price) | -0.4939*** | (0.1250) | -0.3376** | (0.1441) |
| Observed Design Error (ODE) | 0.0007 | (0.0145) | 0.0042 | (0.0142) |
| | | | | |
| Observations | 3,407 | | 3,407 | |
| F-statistic | 5.01 | | 5.12 | |
| P-value (model) | 0.00 | | 0.00 | |

Additional covariates not listed above include age, age$^2$, average age (for the Conditional FE model), education, level of risk aversion, HSNP Village, the Inverse Mills ratio, and a constant. [L] Variable is lagged one period. [#]Omitted variable is E*xpected conditions: poor*. Robust and clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 11.** AME of the interacted variables on IBLI purchase level, conditional on purchasing

| | AME | Std. Err. | t | P>t | Confidence Interval | |
|---|---|---|---|---|---|---|
| **Price =** | **Observed Design Error** | | | | | |
| Mean-1 SD | 0.013 | 0.016 | 0.870 | 0.385 | -0.017 | 0.044 |
| Mean Price | 0.003 | 0.014 | 0.210 | 0.833 | -0.025 | 0.031 |
| Mean +1SD | -0.007 | 0.019 | -0.400 | 0.693 | -0.044 | 0.029 |
| **Observed Design Error=** | **Price** | | | | | |
| Mean-1 SD | -0.212 | 0.214 | -0.990 | 0.322 | -0.631 | 0.208 |
| Mean ODE | -0.319 | 0.151 | -2.110 | 0.035 | -0.615 | -0.023 |
| Mean +1SD | -0.425 | 0.137 | -3.100 | 0.002 | -0.695 | -0.156 |
| **Extension Game** | **Correlation(M,CL)** | | | | | |
| No | -0.403 | 0.138 | -2.920 | 0.004 | -0.674 | -0.132 |
| Yes | 0.300 | 0.187 | 1.600 | 0.109 | -0.067 | 0.666 |

# Appendices

## *Appendix A: Key Features of Index Based Livestock Insurance (IBLI) Contract*

***The risk:***

Index based Livestock Insurance (IBLI) is a product that is designed to protect against drought-related livestock mortality.

***The index:***

As described in Chantarat et al. (2013), the index in IBLI is the predicted livestock mortality rate. It is calculated by using a measure of vegetation coverage that is measured by satellite-based sensors, called the Normalized Difference Vegetation Index (NDVI). This vegetation measure is fed into a statistical response function that was constructed by relating historic drought related livestock mortality data to various transformation of the historic NDVI. The parameters estimated from the historic data are used to predict drought related livestock mortality from sequences of observed NDVI values.

***Contract strike level:***

The index threshold above which payouts are made is called the strike level. The strike level for IBLI is 15%. In other words, IBLI will compensate if predicted livestock mortality is above 15%.

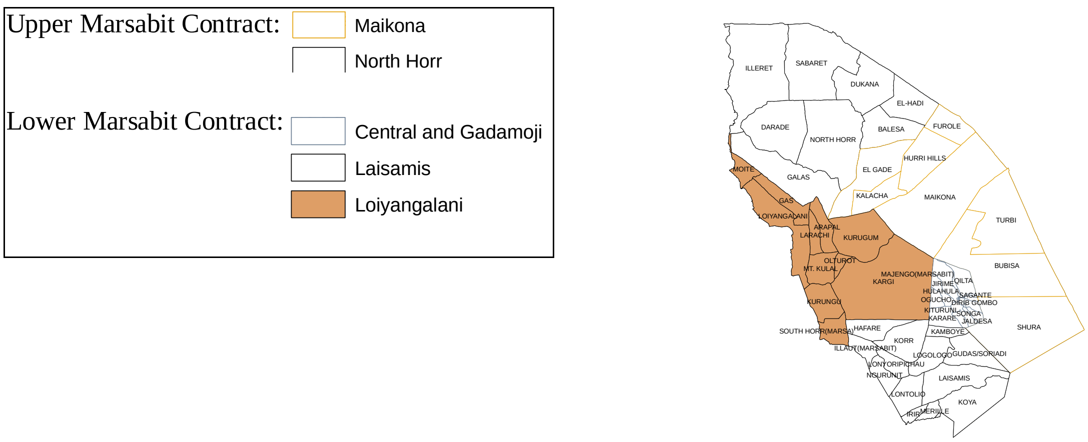
***Geographical coverage of contract and the index:***

Marsabit District is covered by two separate contracts. There is an Upper Marsabit contract consisting of Maikona and North Horr divisions, and a Lower Marsabit contract consisting of Central, Gadamoji, Laisamis, and Loiyangalani divisions (Figure A.1).

The index – predicted livestock mortality – computed and reported at the division level. The five division—North Horr, Maikona, Loiyangalani, Laisamis and Central—could each have a different index level.

Because insurance payments are made according to the index level, this means that IBLI may make different indemnity payments across divisions. Every insurance policy holder within the same division, however, will receive the same rate of insurance payment, provided that the index is above the strike.

**Figure A1**. IBLI Geographical Coverage




***Contract premium rates and indemnity payments:***

Premiums are different between the two contract regions to reflect their differences in historical risk of livestock mortality. Premium rates are reported as a percent of the value of insured livestock. From first initial sales in January of 2010 through 2012, the unsubsidized and loaded premiums were 5.4% and 9.2% in the lower and upper IBLI contract regions, respectively. At that time, those premiums were subsidized by about 40% so that pastoralists in the lower and upper regions purchased IBLI coverage at a rate of 5.5% and 3.25%, respectively.

The standard livestock types for a pastoral herd will be covered: camels, cattle, sheep and goats.

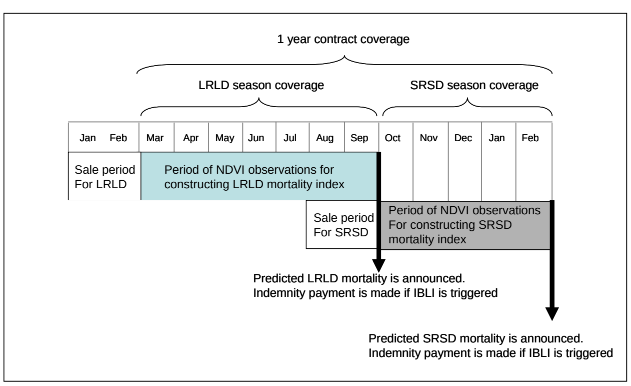
To arrive at a value for the insured herd, the four livestock types will be transformed into a standard livestock unit known as a Tropical Livestock Unit (TLU). TLU is calculated as follows: 1 Camel = 1.4 TLU, 1 Cattle = 1 TLU and 1 goat/sheep = 0.1 TLU. Once total TLU are calculated, the value of the total herd is computed based on average historical prices for livestock across Marsabit, at a set price per TLU insured of Ksh 15,000. The premiums are then applied to the insured value to arrive at the amount one pays for IBLI coverage for the year.

There are no indemnity payments if the index falls below the strike. If the index exceeds the strike, indemnity payments are calculated as the product of the value of the insured herd and difference between the predicted livestock mortality and the deductible.

***Time Coverage of IBLI:***

The figure below presents the time coverage of the IBLI. The annual contract begins at the close of a marketing window, either March 1$^{st}$ or October 1$^{st}$. Contracts are sold only within a two month (January-February of August-September) time frame as the rainy season that typically begins right after that window may give the potential buyer information about the likely range conditions of the season to come that would affect purchase decisions. This annual contract has two potential payout periods: at the end of the long dry season based on the October 1$^{st}$ index reading and at the end of the short dry season based on the March 1$^{st}$ index readings. At these points of time, if the index exceeds 15%, active policy holders receive an indemnity payment.

**Figure A.1.** Temporal Structure of IBLI contract



*Appendix B: Analysis of Attrition*

Attrition rates averaged about 4% per year and the rate of attrition was similar between survey rounds. Table B.1 provides details on the differences between full balanced panel households and those that left. Refer to Table 6 for the variable descriptions. Note that HSNP, coupon, effective price and design error are all related to time so that we expect there to be systematic differences in those variables between those whom we observe in all periods and those that exit, due purely to exogenous factors.

**Table B.1.** Summary statistics for those that stayed and those that left/entered the survey

| | **Full Panel** *(N=833)* | | **Left/Entered** *(N=91)* | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std. Err.** | **Mean** | **Std. Err.** | **Difference** | **t-stat** |
| Gender | 0.58 | 0.04 | 0.57 | 0.09 | -0.02 | -0.16 |
| Age | 4.72 | 0.14 | 4.60 | 0.29 | -0.12 | -0.38 |
| Education | 3.83 | 0.29 | 4.46 | 0.71 | 0.63 | 0.82 |
| Risk aversion: neutral | 0.24 | 0.03 | 0.13 | 0.03 | -0.11 | -2.21 ** |
| Risk aversion: moderate | 0.49 | 0.04 | 0.16 | 0.04 | -0.33 | -5.72 *** |
| Risk aversion: extreme | 0.27 | 0.04 | 0.19 | 0.04 | -0.08 | -1.50 |
| Dependency Ratio | 0.55 | 0.02 | 0.54 | 0.03 | 0.00 | -0.12 |
| Social Groups | 0.55 | 0.04 | 0.57 | 0.11 | 0.02 | 0.16 |
| Asset Index | 0.79 | 0.05 | 0.74 | 0.10 | -0.06 | -0.51 |
| Income (KSH monthly) | 7,855 | 468 | 7,956 | 1,572 | 101 | 0.06 |
| Ratio livestock income | 0.62 | 0.02 | 0.40 | 0.06 | -0.22 | -3.30 *** |
| Herd size | 1.30 | 0.10 | 2.51 | 0.46 | 1.20 | 2.58 ** |
| Livestock mortality rate | 0.15 | 0.01 | 0.18 | 0.02 | 0.03 | 1.29 |
| Savings | 0.09 | 0.01 | 0.06 | 0.02 | -0.03 | -1.15 |
| HSNP | 0.24 | 0.03 | 0.12 | 0.05 | -0.12 | -2.17 ** |
| Expected conditions | 2.87 | 0.06 | 3.22 | 0.15 | 0.35 | 2.17 ** |
| Risk | 0.05 | 0.00 | 0.08 | 0.02 | 0.03 | 1.36 |
| Correlation(M, CL) | 0.46 | 0.02 | 0.75 | 0.06 | 0.28 | 4.21 *** |
| Ln(effective price) | 6.15 | 0.01 | 6.32 | 0.04 | 0.17 | 4.23 *** |
| Design Error | 2.63 | 0.05 | 2.23 | 0.10 | -0.40 | -3.45 *** |
| IBLI game | 0.23 | 0.03 | 0.37 | 0.09 | 0.15 | 1.49 |
| Coupon | 0.59 | 0.02 | 0.68 | 0.09 | 0.09 | 1.04 |

The survey teams used a census of households with herd sizes in order to replace exit households with households from the same wealth stratum. Thus we hope that the exiting and replacement households are similar. Their descriptive statistics are found in Table B.2. As above, most of the systematic differences are likely due to duration of survey participation and likelihood of participating during certain periods rather than actual differences between households. The only variable that is worrisome is herd size, which indicates that replacement households have much smaller herds than those that left. This is most likely a result of over-sampling in the wealthy household strata, which leaves fewer eligible replacements for attrited wealthy households.[65]

[65] Large portions of the middle and high wealth strata were sampled in some smaller communities. In such cases, finding within strata replacement households can be difficult. Pastoral mobility and demand for herding labor far from households and community centers further exacerbates the challenges of replacing households from an already attenuated roster.

**Table B.2.** Summary statistics for entry vs. exit households

| | Exit (N=91) | | Enter (N=91) | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std. Err.** | **Mean** | **Std. Err.** | **Difference** | **t-stat** |
| Gender | 0.57 | 0.09 | 0.67 | 0.07 | 0.10 | 0.87 |
| Age | 4.60 | 0.29 | 5.00 | 0.23 | 0.40 | 1.08 |
| Education | 4.46 | 0.73 | 4.89 | 0.59 | 0.43 | 0.46 |
| Risk aversion: neutral | 0.13 | 0.04 | 0.20 | 0.03 | 0.06 | 1.33 |
| Risk aversion: moderate | 0.16 | 0.04 | 0.15 | 0.03 | -0.01 | -0.12 |
| Risk aversion: extreme | 0.19 | 0.04 | 0.12 | 0.03 | -0.07 | -1.28 |
| Social Groups | 0.57 | 0.11 | 0.71 | 0.11 | 0.14 | 0.86 |
| Dependency Ratio | 0.54 | 0.03 | 0.59 | 0.02 | 0.05 | 1.20 |
| Asset Index | 0.74 | 0.10 | 0.69 | 0.11 | -0.05 | -0.35 |
| Income (Ksh monthly) | 7,956 | 1,610 | 5,739 | 599 | -2,217 | -1.29 |
| Ratio livestock income | 0.40 | 0.06 | 0.46 | 0.04 | 0.06 | 0.81 |
| Herd size | 2.51 | 0.47 | 0.66 | 0.08 | -1.85 | -3.90 *** |
| Livestock mortality rate | 0.18 | 0.03 | 0.16 | 0.02 | -0.02 | -0.64 |
| Savings | 0.06 | 0.02 | 0.05 | 0.01 | -0.01 | -0.31 |
| HSNP | 0.12 | 0.05 | 0.33 | 0.07 | 0.21 | 2.50 ** |
| Expected conditions | 3.22 | 0.16 | 3.25 | 0.09 | 0.03 | 0.16 |
| Risk | 0.08 | 0.02 | 0.07 | 0.02 | -0.01 | -0.47 |
| Correlation(M, CL) | 0.75 | 0.07 | 0.32 | 0.10 | -0.43 | -3.70 *** |
| Ln(effective price) | 6.32 | 0.04 | 6.25 | 0.03 | -0.07 | -1.41 |
| Design Error | 2.23 | 0.10 | 2.28 | 0.09 | 0.05 | 0.35 |
| IBLI game | 0.37 | 0.10 | 0.00 | 0.00 | -0.37 | -3.83 *** |
| Coupon | 0.68 | 0.09 | 0.18 | 0.03 | -0.50 | -5.25 *** |

***Appendix C: Asset Index***

The asset index is constructed by performing a factor analysis on a set of variables meant to capture variation in household wealth. This approach is discussed in Sahn and Stifle (2000). The variables focus on five general categories: household construction materials, household facilities, cooking and lighting fuels, and household durables. Because the list of possible durables is extremely long (more than 70), they are aggregated by value (small, medium, large) and use (productive, other) except for large assets which are divided into those with motors and those without. Categorization was performed by the authors and is clearly not the only method for dividing or aggregating the long list of assets. When in doubt as to which category to place an item, we relied on the frequency of ownership to guild our decision. Table C.1 includes the descriptions of each variable. Table C.2 provides the factor loadings, which were estimated using the variables described in table C.1 and including division year fixed effects.

**Table C.1** Variable used in the factor analysis to generate an asset index

| | |
|---|---|
| Improved Wall | =1 if walls are stone, brick, cement, corrugated iron, mud plastered with cement, or tin |
| Improved Floor | =1 if floor is cement, tile, or wood |
| Improved Toilet | =1 if toilet is flush or covered latrine |
| Improved Light | =1 if main source of lighting is electricity, gas, solar |
| Improved cooking appliance | =1 if main cooking appliance is jiko, kerosene stove, gas cooker, or electric cooker |
| Improved Fuel | =1 if main cooking fuel is electricity, paraffin, gas or charcoal |
| Improved furniture | Total number of the following assets: metal trunks, mosquito nets, modern chairs, modern tables, wardrobes, mattresses and modern beds |
| Water Source: Open | =1 if main water source is river, lake, pond, unprotected well or unprotected spring |
| Water Source: Protected | =1 if main water source is protected spring or protected well |
| Water Source: Borehole | =1 if main water source is a borehole |
| Water source: Tap | =1 if main water source is a public or private tap |
| Water Source: Rainwater catchment | =1 if main water source is a rainwater catchment (usually cement or plastic) |
| Water Source: tanker | =1 if main water source is water tanker (usually associated with NGO and food aid activities during drought) |
| Education | Maximum household education |
| Total cash savings | Total monies held at home, in merry-go-round groups, in micro-finance institutions, in savings and credit cooperatives, in bank accounts, with traders or shops, and in M-Pesa (a mobile-based micro-finance institution) accounts. |
| Land | Hectares owned |
| Irrigation | =1 if household owns irrigated land |
| Poultry | Number of chickens |
| Donkeys | Number of donkeys |
| Very small | Total number of the following assets: gourds, cups, scissors, and needle and thread sets. |
| Small tools | Total number of the following assets: anvils, panier, sickle, pickaxe, hoe, spade, machetes, spears, bows, club, chisels, hammers, files, fishing lines. |
| Small other | Total number of the following assets: musical instruments, traditional tools, bells, knifes, basins, sufirias, thermoses, buckets, wristwatches, jewelry |
| Medium tools | Total number of the following assets: Wheelbarrows, fishing nets, mobile phones, washing machines, spinning machines, weaving machines, sewing machines, bicycles, and plows. |
| Medium other | Total number of the following assets: water tank, jerry can, paraffin lamp, water drum, kerosene stove, charcoal stoves, ovens and radios. |
| Large | Total number of the following assets: animal carts, shops, stalls and boats. |
| Large with motor | Total number of the following assets: cars, motorbikes and tractors. |

**Table C.2** Factor loadings used to generate the asset index

| Variables | Factor Loading |
|---|---|
| Improved Wall | 0.132 |
| Improved Floor | 0.130 |
| Improved Toilet | 0.128 |
| Improved Light | 0.118 |
| Improved cooking appliance | 0.077 |
| Improved Fuel | 0.064 |
| Improved furniture | 0.165 |
| Water Source: Open | 0.004 |
| Water Source: Protected | 0.004 |
| Water Source: Borehole | -0.008 |
| Water source: Tap | 0.040 |
| Water Source: Rainwater catchment | 0.079 |
| Water Source: Tanker | 0.021 |
| Education | 0.121 |
| Total cash savings | 0.085 |
| Land | 0.051 |
| Irrigation | 0.033 |
| Poultry | 0.081 |
| Donkeys | 0.018 |
| Very small | 0.040 |
| Small tools | 0.126 |
| Small other | 0.053 |
| Medium tools | 0.164 |
| Medium other | 0.135 |
| Large | 0.037 |
| Large with motor | 0.089 |

Division*period dummies included in the factor analysis.

***Appendix D: Validity of Excludable Variable.***

We include a dummy variable to indicate that the household received a discount coupon in the first stage selection equation but exclude it from the demand equation. The selection equation estimates found in Table E1 and Table 8 clearly indicate that receiving a coupon has a large, positive, and statistically significant impact on the likelihood of purchasing IBLI, even after accounting for size of the discount the coupon offered ($\beta$=0.9866, $p<0.01$). This effect seems purely a randomized treatment that should be irrelevant to purchase volume conditional on uptake. So that variable seems a strong candidate for exclusion from the second stage estimation of uptake volume.

Although there is no agreed upon method for testing excludability of a candidate instrument and it seems to rarely be done with selection models, we venture to provide some statistical support that the exclusion of that indicator variable does not cause bias in the demand equation estimates. Because we only have one exclusion variable, our tests rest on identification through nonlinearity on the probit model, which is likely to be very weak. First, we include the coupon dummy variable in the second stage regression. The coefficient on the coupon dummy is negative and statistically insignificant (beta=-0.122, p-value=0.366). Comparing this set of estimates with those estimated with the coupon dummy excluded, we fail to reject the null hypothesis that the joint change to remaining estimates is zero ($\chi^2(45)=1.62$, p-value=1.00). More specifically, we would expect a large change between the two models in the estimated parameter on the effective price if the receiving a coupon played an important role in determining levels of demand beyond providing a price discount. Testing for a difference in the two price parameter estimates, we cannot reject the null of no change ($\chi^2(1)=0.87$, p-value=0.352). Of course, this does not mean that the variable should be omitted, only that it has little independent effect on the level of purchase and does not result in large shifts in parameter values when included.

We can also check if the errors estimated by the demand equation without the coupon dummy vary by coupon status. Because selection is controlled for through the inverse Mills ratio and coupons were randomly distributed, there should be no omitted variable bias in the demand equation parameter estimates except potentially in effective price, but that bias was ruled out in step one. A t-test of the demand residuals over the coupon status does not reject the null of equal errors between those who received a coupon and those who did not (difference=0.054, t-statistic(529)=0.756).

***Appendix E. Coefficient Estimates of Uptake and Demand for ILBI***

**Table E1.** Coefficient estimates for probit selection

| | Pooled | | Conditional FE | |
|---|---|---|---|---|
| VARIABLES | Coefficient | Std. Err. | Coefficient | Std. Err. |
| *Household Period-Specific Characteristics:* | | | | |
| Male | 0.2160* | (0.1287) | 0.2251* | (0.1268) |
| Dependency Ratio | -0.5756** | (0.2909) | 0.0095 | (0.4881) |
| Social Groups $^{L}$ | 0.0826 | (0.0577) | 0.0074 | (0.0679) |
| Asset Index $^{L}$ | -0.5396** | (0.2108) | -0.3285** | (0.1413) |
| Asset Index$^{2\ L}$ | 0.0844*** | (0.0308) | 0.2140** | (0.1048) |
| Ln(income) $^{L}$ | -0.0371 | (0.0724) | -0.0454 | (0.0319) |
| Ln(income)$^{2\ L}$ | 0.0006 | (0.0069) | 0.0058 | (0.0070) |
| Ratio income livestock $^{L}$ | -0.3127* | (0.1675) | 0.0158 | (0.1739) |
| TLU $^{L}$ | 0.0798 | (0.0891) | 0.1193* | (0.0624) |
| TLU$^{2\ L}$ | -0.0143 | (0.0102) | -0.0417* | (0.0218) |
| Livestock Mortality Rate $^{L}$ | 0.0002 | (0.2214) | 0.2155 | (0.2299) |
| Savings (10TLU) $^{L}$ | 0.0156 | (0.2729) | -0.3324* | (0.1993) |
| HSNP $^{L}$ | 0.3163** | (0.1321) | 0.3164** | (0.1264) |
| *Household Averages Characteristics:* | | | | |
| Dependency Ratio | | | -0.8367*** | (0.3159) |
| Social Groups | | | 0.2262** | (0.1036) |
| Asset Index | | | -0.0648 | (0.1338) |
| Ln(income) | | | -0.0079 | (0.0522) |
| Ratio income livestock | | | -0.1974 | (0.2659) |
| TLU | | | -0.0050 | (0.0409) |
| Livestock Mortality Rate | | | -0.7840 | (1.2210) |
| Savings (10TLU) | | | -0.4752 | (0.3961) |
| Expected Rangelands: Good# | | | -0.1310 | (0.4096) |
| Expected Rangelands: Normal# | | | -0.2549 | (0.3446) |
| *Prospective Adverse Selection:* | | | | |
| Expected conditions: Good# | -0.2933** | (0.1292) | -0.2165 | (0.1479) |
| Expected conditions: Normal# | -0.0825 | (0.1342) | -0.0368 | (0.1432) |
| Pre-CZNDVI | -0.0007 | (0.0085) | -0.0016 | (0.0085) |
| Division Livestock Mortality | 0.2819** | (0.1246) | 0.3168*** | (0.1180) |
| Division Risk | -0.2653* | (0.1421) | -0.3486*** | (0.1347) |
| Division Correlation | 1.3538 | (1.0485) | 1.6954* | (1.0297) |
| *Product Related Characteristics :* | | | | |
| Existing IBLI Coverage | -0.2716 | (0.2822) | -0.3386 | (0.3239) |
| Risk | -3.4697*** | (1.2608) | -1.5983 | (2.0626) |
| Correlation | 0.1485 | (0.1569) | 0.1606 | (0.1556) |
| Extension Game | -0.0759 | (0.1752) | -0.0397 | (0.1747) |
| Correlation X Game | 0.1151 | (0.3485) | 0.1289 | (0.3404) |
| Ln(price) | 0.4209 | (0.3186) | 0.3647 | (0.2831) |
| Observed Design Error (ODE) | 0.4850** | (0.2277) | 0.4887* | (0.2500) |
| Ln(price) X ODE | -0.0874** | (0.0385) | -0.0885** | (0.0424) |
| Coupon Dummy | 1.0114*** | (0.2023) | 0.9866*** | (0.1815) |
| | | | | |
| Observations | 3,407 | | 3,407 | |
| F-statistic | 5.01 | | 5.12 | |
| P-value (model) | 0.00 | | 0.00 | |

Additional covariates not listed above include age, age$^2$, average age (for the Conditional FE Model), education, level of risk aversion, HSNP Village, and a constant. $^{L}$ Variable is lagged one period. #Omitted variable is E*xpected conditions: poor*. Robust and clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table E2.** Estimated demand coefficients, conditional on purchase

| | Pooled | | Conditional FE | |
|---|---|---|---|---|
| VARIABLES | Coefficient | Std. Err. | Coefficient | Std. Err. |
| *Household Period-Specific Characteristics:* | | | | |
| Male | 0.0953 | (0.0925) | 0.1309 | -0.0968 |
| Dependency Ratio | -0.2689 | (0.2654) | 0.4853 | -0.7027 |
| Social Groups $^{L}$ | 0.0296 | (0.0508) | -0.0206 | -0.0582 |
| Asset Index $^{L}$ | 0.0478 | (0.1432) | 0.2276** | -0.0991 |
| Asset Index $^{2\ L}$ | 0.0113 | (0.0200) | -0.0799 | -0.0716 |
| Ln(income) $^{L}$ | 0.1559* | (0.0841) | 0.0408* | -0.0242 |
| Ln(income) $^{2\ L}$ | -0.0090 | (0.0066) | -0.0115* | -0.0064 |
| Ratio income livestock $^{L}$ | -0.4859*** | (0.1788) | -0.5312*** | -0.1773 |
| TLU $^{L}$ | 0.1127* | (0.0684) | 0.1387** | -0.0629 |
| TLU $^{2\ L}$ | -0.0099 | (0.0086) | -0.0105 | -0.0121 |
| Livestock Mortality Rate $^{L}$ | 0.2142 | (0.2599) | 0.096 | -0.2071 |
| Savings (10TLU) $^{L}$ | 0.3334*** | (0.1231) | 0.4070** | -0.1796 |
| HSNP $^{L}$ | -0.0652 | (0.0990) | -0.2116* | -0.1176 |
| *Household Averages Characteristics:* | | | | |
| Dependency Ratio | | | -0.4331 | -0.2735 |
| Social Groups | | | 0.0887 | -0.081 |
| Asset Index | | | 0.1845** | -0.0896 |
| Ln(income) | | | 0.0154 | -0.039 |
| Ratio income livestock | | | -0.1099 | -0.2156 |
| TLU | | | 0.0291 | -0.0571 |
| Livestock Mortality Rate | | | -0.3814 | -0.8374 |
| Savings (10TLU) | | | -0.0017 | -0.2467 |
| Expected Rangelands: Good# | | | -0.9935*** | -0.2847 |
| Expected Rangelands: Normal# | | | -0.8714*** | -0.2905 |
| *Prospective Adverse Selection:* | | | | |
| Expected conditions: Good# | -0.4408*** | (0.1012) | -0.2646** | (0.1086) |
| Expected conditions: Normal# | -0.3824*** | (0.1125) | -0.1584 | (0.0990) |
| Pre-CZNDVI | -0.0017 | (0.0047) | -0.0106 | (0.0066) |
| Division Livestock Mortality | -0.2587*** | (0.0916) | -0.2168** | (0.0864) |
| Division Risk | 0.2775*** | (0.1040) | 0.2672*** | (0.0990) |
| Division Correlation | -1.2798 | (0.7901) | -1.0515 | (0.7112) |
| *Product Related Characteristics :* | | | | |
| Existing IBLI Coverage | 0.0094 | (0.1870) | -0.0612 | -0.1961 |
| Risk | -1.2195 | (1.2359) | 0.9285 | -1.5273 |
| Correlation | -0.3950*** | (0.1282) | -0.4030*** | -0.1379 |
| Extension Game | -0.2221 | (0.1396) | -0.2025 | -0.1341 |
| Correlation X Game | 0.7302*** | (0.2448) | 0.7025*** | -0.2434 |
| Ln(price) | -0.3152 | (0.2184) | -0.1907 | -0.229 |
| Observed Design Error (ODE) | 0.1939 | (0.1642) | 0.1630 | -0.1441 |
| Ln(price) X ODE | -0.0321 | (0.0269) | -0.0264 | -0.0241 |
| | | | | |
| Observations | 3,407 | | 3,407 | |
| F-statistic | 5.01 | | 5.15 | |
| P-value (model) | 0.00 | | 0.00 | |

Additional covariates not listed above include age, age$^2$, average age (Conditional FE Model), education, level of risk aversion, HSNP Village, inverse Mills Ratio, and a constant. $^{L}$ Variable is lagged one period. #Omitted variable is E*xpected conditions: poor*. Robust and clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

### *Appendix F: Shapley Goodness of Fit Decomposition*

A Shapley's goodness of fit (GOF) decomposition is used to determine the level of variation in demand that is captured by categories of variables (Kolenikov 2000; Shapley 1953; Shorrocks 2013).[66] The variable categories include: household demographics, household finances, prospective intertemporal adverse selection, prospective spatial adverse selection, idiosyncratic risk & knowledge, design risk & price, other, and the instrument variable. A two-stage Heckman approach, rather than the maximum likelihood approach used in the main body of the paper, is used here in order to examine the contributions of the variable groups in both the uptake and demand analysis. In addition, we use the pooled, rather than conditional fixed effects, approach here in order to reduce the computational burden. Notice that the pooled and conditional fixed effects estimates are generally very similar.

Tables F1 and F2 include the two-stage estimates and estimated group contributions to each stage's (uptake and level of purchase) GOF. The pooled maximum likelihood estimates from the Heckman selection model (from Table E1 and Table E2) are also included as evidence that the two models result in very similar estimates and that the decomposition of the two-stage estimates are likely to be reflective of the contributions in the maximum likelihood Heckman model.[67]

Household characteristics clearly play a role in uptake but are unable to account for even half of the variation captured by the model (Table F1). Temporal and spatial adverse selection provide similar contributions and their combined impacts are similar to that of the relative importance of covariate risk. The three design risk and price variables account for 18% of the Pseudo $R^2$ measure, more than any other group except for our instrumental variable.

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[66] We use the STATA user-written command *shapley2* (Juárez 2014).

[67] The ML Heckman estimates are generated in a single step so that we cannot examine the goodness of fit contributions in each process separately.

The role of adverse selection in the fit of our model is greater for level of demand than uptake. Conversely, the role of design risk and price has fallen considerably. In addition, income and wealth have become much more important while the importance of covariate risk has changes very little.

In summary, the total contribution made by adverse selection and product related characteristics towards the GOF are greater than that of a large set of familiar household characteristics in both uptake and level of demand models. Our models would perform much worse with these crucial estimates of basis risk and adverse selection.

**Table F1.** Decomposition of Pseudo $R^2$ for uptake probit

| VARIABLES | Heckman ML Probit Coefficient | Heckman ML Probit Std. Err. | 2 Step Probit Coefficient | 2 Step Probit Std. Err. | Shapley Decomposition of Pseudo $R^{2}$ [A] |
|---|---|---|---|---|---|
| *Household Period-Specific Characteristics:* | | | | | |
| **Demographics:** [B] | | | | | 12.92 % |
| Male | 0.2160* | (0.1287) | 0.2166 | (0.1350) | |
| Dependency Ratio | -0.5756** | (0.2909) | -0.5868* | (0.3019) | |
| Social Groups [L] | 0.0826 | (0.0577) | 0.0910 | (0.0593) | |
| **Financial:** | | | | | 14.70 % |
| Asset Index [L] | -0.5396** | (0.2108) | -0.4800** | (0.2122) | |
| Asset Index$^2$ [L] | 0.0844*** | (0.0308) | 0.0854** | (0.0349) | |
| Ln(income) [L] | -0.0371 | (0.0724) | -0.0477 | (0.0776) | |
| Ln(income)$^2$ [L] | 0.0006 | (0.0069) | 0.0022 | (0.0075) | |
| Ratio income livestock [L] | -0.3127* | (0.1675) | -0.3546* | (0.1949) | |
| TLU [L] | 0.0798 | (0.0891) | 0.0784 | (0.0908) | |
| TLU$^2$ [L] | -0.0143 | (0.0102) | -0.0138 | (0.0105) | |
| Livestock Mortality Rate [L] | 0.0002 | (0.2214) | 0.0060 | (0.2247) | |
| Savings (10TLU) [L] | 0.0156 | (0.2729) | -0.3003 | (0.2014) | |
| HSNP [L] | 0.3163** | (0.1321) | 0.3034** | (0.1369) | |
| *Prospective Adverse Selection:* | | | | | |
| **Intertemporal:** | | | | | 3.55 % |
| Expected conditions: Good[#] | -0.2933** | (0.1292) | -0.3192** | (0.1335) | |
| Expected conditions: Normal[#] | -0.0825 | (0.1342) | -0.1030 | (0.1355) | |
| Pre-CZNDVI | -0.0007 | (0.0085) | -0.0012 | (0.0088) | |
| **Spatial:** | | | | | 3.37 % |
| Division Livestock Mortality | 0.2819** | (0.1246) | 0.2881** | (0.1274) | |
| Division Risk | -0.2653* | (0.1421) | -0.2784* | (0.1474) | |
| Division Correlation | 1.3538 | (1.0485) | 1.4687 | (1.0858) | |
| *Product Related Characteristics :* | | | | | |
| **Idiosyncratic Risk & Knowledge:** | | | | | 6.51 % |
| Risk | -3.4697*** | (1.2608) | -3.4147*** | (1.3138) | |
| Correlation | 0.1485 | (0.1569) | 0.1322 | (0.1585) | |
| Extension Game | -0.0759 | (0.1752) | -0.0922 | (0.1830) | |
| Correlation X Game | 0.1151 | (0.3485) | 0.1267 | (0.3608) | |
| **Design Risk & Price:** | | | | | 17.97 % |
| Ln(price) | 0.4209 | (0.3186) | 0.3959 | (0.3032) | |
| Observed Design Error (ODE) | 0.4850** | (0.2277) | 0.4639** | (0.2239) | |
| Ln(price) X ODE | -0.0874** | (0.0385) | -0.0841** | (0.0379) | |
| **Instrumental Variable:** | | | | | 36.95 % |
| Coupon Dummy | 1.0114*** | (0.2023) | 1.006*** | (0.2080) | |
| | | | | | |
| Observations | 3,407 | | 3,407 | | |
| F-statistic [Wald $\chi^2$] | 5.01 | | [140.04] | | |
| P-value (model) | 0.00 | | 0.00 | | |
| Pseudo R2 | | | 0.1824 | | |

[A] The Shapley decomposition is performed on eight groups of variables indicated by the bold labels on the left using the 2-stage probit estimates. A group containing existing IBLI coverage and an indicator that the household is in an HSNP targeted community was also included in the regressions and decomposition; its Shapley contribution was 4.02%. [B] Additional covariates in the demographics group include age, age$^2$, education, level of risk aversion. [L] Variable is lagged one period. [#]Omitted variable is E*xpected conditions: poor*. Robust and clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table F2.** Decomposition of $R^2$ for level of purchase, conditional on purchase

| | Demand (MLE) | | Demand (2 Step) | | Shapley |
|---|---|---|---|---|---|
| VARIABLES | Coefficient | Std. Err. | Coefficient | Std. Err. | Decomposition of Pseudo R2 [A] |
| *Household Period-Specific Characteristics:* | | | | | |
| **Demographics:** [B] | | | | | 13.83% |
| Male | 0.0953 | (0.0925) | 0.0689 | (0.1071) | |
| Dependency Ratio | -0.2689 | (0.2654) | -0.2475 | (0.2878) | |
| Social Groups [L] | 0.0296 | (0.0508) | 0.0297 | (0.0550) | |
| **Financial:** | | | | | 30.64 |
| Asset Index [L] | 0.0478 | (0.1432) | 0.0766 | (0.1689) | |
| Asset Index$^2$ [L] | 0.0113 | (0.0200) | 0.0055 | (0.0269) | |
| Ln(income) [L] | 0.1559* | (0.0841) | 0.1609* | (0.0921) | |
| Ln(income)$^2$ [L] | -0.0090 | (0.0066) | -0.0091 | (0.0073) | |
| Ratio income livestock [L] | -0.4859*** | (0.1788) | -0.5384*** | (0.2039) | |
| Livestock Mortality Rate [L] | 0.2142 | (0.2599) | 0.2072 | (0.2825) | |
| TLU [L] | 0.1127* | (0.0684) | 0.0999 | (0.0754) | |
| TLU$^2$ [L] | -0.0099 | (0.0086) | -0.0078 | (0.0093) | |
| Savings (10TLU) [L] | 0.3334*** | (0.1231) | 0.2469 | (0.2049) | |
| HSNP [L] | -0.0652 | (0.0990) | -0.0572 | (0.1081) | |
| *Prospective Adverse Selection:* | | | | | |
| **Intertemporal:** | | | | | 16.32% |
| Expected conditions: Good[#] | -0.4408*** | (0.1012) | -0.4589*** | (0.1090) | |
| Expected conditions: Normal[#] | -0.3824*** | (0.1125) | -0.3765*** | (0.1190) | |
| Pre-CZNDVI | -0.0017 | (0.0047) | 0.0016 | (0.0055) | |
| **Spatial:** | | | | | 16.02% |
| Division Livestock Mortality | -0.2587*** | (0.0916) | -0.2655*** | (0.1005) | |
| Division Risk | 0.2775*** | (0.1040) | 0.2803** | (0.1141) | |
| Division Correlation | -1.2798 | (0.7901) | -1.3228 | (0.8606) | |
| *Product Related Characteristics :* | | | | | |
| **Idiosyncratic Risk & Knowledge:** | | | | | 10.48 % |
| Risk | -1.2195 | (1.2359) | -1.3254 | (1.3598) | |
| Correlation | -0.3950*** | (0.1282) | -0.4310*** | (0.1422) | |
| Extension Game | -0.2221 | (0.1396) | -0.2450* | (0.1483) | |
| Correlation X Game | 0.7302*** | (0.2448) | 0.7502*** | (0.2634) | |
| **Design Risk & Price:** | | | | | 10.26% |
| Ln(price) | -0.3152 | (0.2184) | -0.3153 | (0.2346) | |
| Observed Design Error (ODE) | 0.1939 | (0.1642) | 0.1654 | (0.1851) | |
| Ln(price) X ODE | -0.0321 | (0.0269) | -0.0265 | (0.0307) | |
| | | | | | |
| Observations | 3,407 | | 547 | | |
| F-statistic | 5.01 | | 5.16 | | |
| P-value (model) | 0.00 | | 0.00 | | |
| $R^2$ | | | 0.3389 | | |

[A] The Shapley decomposition is performed on seven groups of variables indicated by the bold labels on the left. A group containing existing IBLI coverage, an indicator that the household is in an HSNP targeted community, and the inverse Mills Ratio was also included in the regressions; its Shapley contribution was 2.45%. [B] Additional covariates in the demographics group include age, age$^2$, education, level of risk aversion. [L] Variable is lagged one period. [#]Omitted variable is E*xpected conditions: poor*. Robust and clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

# Chapter 4: Impacts of Index Insurance and Cash Transfers

Co-Authored with Andrew G. Mude and Christopher B. Barrett.

## Introduction

For poor rural households in developing countries, the risk of economic, climatic, social, or other shocks to their livelihoods is a daily threat, and can be a devastating reality. The prospect of such shocks drives households to pursue risk-reducing strategies, often at the cost of significant foregone income (Carter 1997; Morduch 1995; Rosenzweig & Binswanger 1993). When shocks do happen, they not only reduce household income but can compel coping behaviors with long-term negative implications, like distress sale off productive assets, withdrawal of children from school, or reducing nutrient intake by skipping meals. Such ex ante and ex post risk management strategies can trap families in cycles of poverty.[68]

Development agencies and governments have been quite active in the past decade or two with interventions that aim to address these structural challenges. Social protection programs are gaining acceptance as a cost-effective strategy for alleviating poverty and vulnerability in developing nations.[69] Although these programs use many different approaches, they commonly emphasize risk and vulnerability reduction among the poor (Conway, de Haan & Norton 2000).

Social assistance, which transfers resources, and social insurance, which supports access to risk pooling, are two distinct, common approaches to social protection. While much has been learned about the impacts of social assistance in the form of cash transfers, much less is known about how those impacts compare

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[68] See the broad range of literature on poverty traps, for example Azariadis & Stachurski (2005); Barrett & Swallow (2006); Barrett & Carter (2013); Bowles, Durlauf & Hoff 2006; Carter & Barrett (2006).

[69] For example, in 2007 the *G8 Summit Declaration on Freedom of Investment, Investment Environment and Social Responsibility* stated that "[s]ocial protection is an investment in a country's economic future and a cost-effective way of fighting poverty" (paragraph 28).

with alternative programs such as insurance. Yet, to fully understand the effectiveness of a specific program or approach we must also take into account the opportunity costs of diverting funds from other potential programs that could also yield welfare gains.

This study compares two social protection programs, examining their behavioral and welfare effects on participants and then situating those impacts in light of their marginal costs to the public through government and donor funding. More precisely, we study the impacts in northern Kenya of the Hunger Safety Net Program (HSNP), a publically funded and administered cash transfer program, and Index Based Livestock Insurance (IBLI), a privately administered but publically supported livestock insurance program. Although both programs were introduced contemporaneously with the aim to improve lives in northern Kenya, the country's poorest region, they take markedly different approaches. The government-run, donor-funded HSNP provides targeted participants with a regular source of income. IBLI is private and provides commercial policy holders with indemnity payments to compensate for irregular, catastrophic losses of livestock, the main productive asset. Using four years' household panel data, 2009-12, and the known targeting criteria of HSNP and the randomization of inducements to purchase IBLI, we compare the causal impacts of each program, explore prospective interaction effects between them, and assess their benefits along specific household characteristics per unit cost of each program.

We find that households with IBLI coverage increase investments in livestock health services, reduce herd size, and see a large increase in milk productivity and milk income. Insured households also increase livestock off take during seasons with low livestock mortality rates. These results point towards reduced precautionary savings among the insured, leading to greater intensification through yield increasing investments. IBLI coverage leads to improved welfare as measured by income per adult equivalent (AE). In comparison, HSNP participation increases the likelihood that a household is partially or fully mobile, and within a few seasons of participating households enjoy reduced livestock mortality rates. In the pastoral region of northern Kenya, mobility and livestock survival are crucial factors for household well-being. Although longer-term HSNP participants also see increased milk productivity, these impacts have yet to express themselves in broader indicators of household welfare. There is little evidence that being a client of both programs improves outcomes examined here although this may be because there is only minor overlap in coverage between the two programs. Finally, an analysis of the relative costs of household responses to the programs finds that the two programs produce average benefits that are similar in magnitude per project dollar while IBLI produces greater benefits with respect to the marginal cost of an additional client.

The remainder of this paper is organized as follows. Section 2 provides background materials on cash transfers and index insurance in order to place our findings in the context of the existing literature. Section 3 provides background on pastoralists in northern Kenya and describes the IBLI product and the HSNP. Section 4 describes the data. Section 5 describes the empirical strategy that is used. Results and a discussion are found in section 6.

## Background

### *Cash Transfers*

One type of social assistance program—cash transfer programs—aims to address poverty by providing cash to the poor or vulnerable, guaranteeing them a minimum level of stable income. Cash transfers are meant to reduce poverty and vulnerability by increasing and smoothing household income. In theory, regular payments can help maintain basic levels of consumption, reduce the use of detrimental risk mitigation strategies, diminish reliance on destructive short-term coping mechanisms, and maintain investments in human capital.

A number of large-scale, long-term, and well-documented social transfer programs (e.g., Mexico's *Progressa/Oportunidades,* South Africa's Child Support Grant program, Brazil's *Bolsa Familia*, Colombia's *Familias en Acción*) have advanced our understanding of transfer programs. In a survey of over 25 cash transfer programs, Fiszbein and Schady (2009) find that transfers significantly reduced the poverty gap in Colombia, Honduras, Mexico, and Nicaragua. They also find evidence from multiple countries that transfer programs can have a variety of socially beneficial impacts on recipients, such as increasing household consumption, increasing enrollment of children in school, reducing the negative impacts of catastrophic shocks, and increasing the bargaining power of women. These changes can both help to reduce the number of households that fall into poverty and to increase the number of households that climb out of poverty (Arnold, Conway & Greenslade 2011).

However, less is known about the behavioral process by which transfers produce welfare impacts. Gertler, Martinez and Rubio-Codina (2012) provide some insight in this area by examining how transfers effect production and investment decisions by *Oportunidades* participants in Mexico. They study finds that transfers increase investments in agricultural assets and leading to an observed increase in agricultural productivity and income. Similar results have been found elsewhere (e.g., in Malawi [Covarrubias, Davis & Winters 2012], Niger [Stoeffler & Mills 2014]), but are far from ubiquitous.

In addition to the direct effects that cash transfers have on current income, the promise of regular future transfers may also relax insurance constraints. Bianchi and Bobba (2012) find that participation in *Oportunidades* increases the likelihood of entering entrepreneurship and that the effect is more tightly linked to the promise of future transfers than to received transfers. Bianchi and Bobba argue that the cash transfers provide a buffer against future income variation, inducing greater risk taking among participants.

Costs are one of the primary drawbacks of transfer programs. The public must shoulder not only the transfer itself but also the administrative and program costs associated with targeting, monitoring, and dispersing transfers. Targeting and monitoring costs can be substantial as they require up-to-date household-level data to determine eligibility. In addition, policy makers and the general public may balk at the prospect of beginning an entitlement program that can be difficult to end (Cain 2011). To have enduring impacts, transfers must either be perpetual or large and sustained to the extent that people can lift themselves out of poverty and become able to self-insure against future shocks.

***Social Insurance***

Weather related risk and shocks are major drivers of the high levels of poverty observed among smallholder farmers in developing countries. Many experts argue that insurance protecting against weather related shocks could help households cope with this risk (e.g., Alderman & Haque 2007; Barnett, Barrett & Skees 2008; Devereux 2001; Mahul & Stutley 2010). Reduced risk exposure through insurance could free households from the need to practice costly self-insurance and protect them from shocks that might drive them into long-term destitution, while encouraging investment or adoption of newer technologies that they perceive as risky.

Socially supported or provided weather index insurance offers an alternative approach to social protection that has, like cash transfers, ignited considerable interest. Index products are designed to overcome supply side barriers thought to hinder access to conventional indemnity insurance for smallholder farmers in developing countries. Indices based on easy-to-observe signals that are likely to be highly correlated with agricultural catastrophes—such as precipitation or temperature—can be used to provide insurance with low overhead. In addition, index based polices are less burdened with monitoring and validation costs, obviate incentives for moral hazard, and may reduce the incidence of adverse selection.

Although index products seem promising, the past decade's wave of index insurance pilot programs have little to show in the way of empirically based impact research. Partially due to low demand and partially due to inadequate data, the research on welfare outcomes due to index insurance coverage is scarce. To the authors' knowledge, there are just three papers that examine outcomes associated with index insurance coverage in developing countries. Two of them examine weather insurance for crops. Mobarak and Rosenzweig (2012) use an intent to treat approach to find that offering index insurance to rice farmers in India increases their likelihood of planting a higher risk/higher yield variety of rice. Karlan et al. (2014) find that Ghanaian farmers with rainfall index insurance increase investments in agriculture and that this response is much greater than in a comparable cohort of households that received a sizable cash grant.[70] The implication is that agricultural investments are risk constrained in this population and that index insurance successfully relaxes that constraint, arguably more effectively than cash transfers.

Janzen and Carter (2013) study the same index based livestock insurance (IBLI) product in Kenya that we explore. They find that, in the wake of indemnity payments triggered by a massive drought, wealthy households with insurance foresee selling fewer livestock (their main productive capital) than their uninsured counterparts and that poor insured households expect to reduce consumption less than the uninsured poor.[71] In addition, Janzen and Carter find evidence that households with insurance are better able to smooth consumption during the drought (pre-indemnity) than the uninsured.

This evidence withstanding, the generally low product uptake and the lack of rigorous impact evaluations has led some to question the building excitement around index insurance and has elicited criticism of the amount of funding that has been directed towards index insurance. According to Binswanger-Mkhize's (2012) "Is There Too Much Hype about Index Based Agricultural Insurance?", it is not surprising that

[70] The Karlan et al. (2014) study is somewhat unique in that uptake was much higher than in other studies. The study also includes randomized cash and insurance grants, which help to identify if households are risk or cash constrained.
[71] Neither effect (change in distress sales/consumption) is apparent in the alternative (poor/rich) population due to insurance.

demand for insurance is low, since better-off farmers already have successful risk mitigation strategies while poorer farmers are unable to afford the insurance or unwilling to experiment with untested new products. Implicit in this argument is that even if index insurance does help people, only a small segment of the population will benefit and it is unlikely to help the poorest. In addition, as nearly all studies of index insurance point out, households that have index insurance coverage almost certainly continue to be exposed to basis risk, which can be quite sizable (Jensen, Barrett & Mude 2014; Leblois, Quirion & Sultan 2014).

## Setting and Interventions

This research examines the impact of two interventions undertaken concurrently among pastoralist households in the arid and semi-arid region of Marsabit in northern Kenya. This section begins with background on pastoralists in this region in order to better place the interventions and their potential outcomes in both welfare and behavioral dimensions. We then provide a description of the HSNP and IBLI programs and their respective costs.

### *Pastoralist in Arid and Semi-Arid Lands*

Greater than half of the earth's surface is arid or semi-arid, and for much of it grazing is the only suitable low-input method for food production (Child et al. 1984).[72] Characterized by a dependence on livestock grazing for a large percent of the household economic portfolio, pastoralism has evolved as a livelihood strategy in many arid and semi-arid lands where cropping is precarious and low concentrations of resources have held population densities low (FAO 2001; Naimir-Fuller 1999). Although livestock provide a means for pastoralists to generate a livelihood in marginal landscapes, they also come with risks. Because they are

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[72] Arid and Semi-Arid Lands (ASAL) are defined by those areas where annual precipitation falls between 0-300 mm and 300-600 mm respectively (FAO 1987). Areas receiving below 500 mm of annual are generally unsuitable for cropping, suitable only for rangelands (Brown 1963).

the most productive asset one can own, livestock usually constitute a large portion of a household's wealth, making it vulnerable to climate shocks and disease.

Among pastoralists in northern Kenya, greater herd size is associated with both higher per capita income and lower income variation (McPeak, Little & Doss 2011). Greater pre-drought herd size is also associated with increased post-drought herd size (Lybbert et al. 2004; McPeak 2005, Barrett et al. 2006), indicating that herd accumulation is both a rational economic investment and an effective strategy for ensuring that the household can rebuild its productive capital after climate shocks. In addition, herd size may reflect a precautionary savings response to uncertainty in environments with incomplete financial markets such as northern Kenya.

Transhumant pastoralists are distinguished by regular cyclical movements of herds between seasonal pastures. Often households will split, part of the household moving a portion of the herd to seasonal, satellite pastures while the rest remains at a base camp. Livestock mobility associated with the satellite camps provides low-cost fodder, contributes to pasture sustainability by allowing degraded pastures near base camps to rest, manages risk, and provides access to different markets (Niamir-Fuller 2005). Where pastures are open or common, satellite herds are free to practice opportunistic grazing and forage tracking, which has been found to increase average herd productivity, reduce production variability due to climate shocks (Niamir-Fuller 1999; Scoones 1994), and increase drought survival rates in northern Kenya (Little el al. 2008). McPeak et al. (2011) find that mobility can impact both rates of loss and causes of loss.

Herd size and mobility are closely related and appear to play an important role in the long-term well-being of pastoralist households. Accessing the benefits of mobility requires labor to tend the satellite herd and removes livestock resources from the base camp (Toth forthcoming). Because herders generally depend on livestock milk and blood to meet their consumption needs, households must have a sufficiently large herd to maintain enough animals in satellite camp to sustain the herders. For households with few livestock or little labor, the costs of mobility are typically too high. The result can be that households with small herds are unable to take full advantage of a primary asset of ASAL, extensive common pool rangelands. In both Ethiopia and Kenya, sedentary households, small herds, and extreme poverty are inextricably associated due to the feedback between mobility and herd size in an environment where there are few other livelihood options (Barrett et al. 2006; Lybbert et al 2004; Little et al. 2008). Furthermore, households that are very poor or have very few animals are less likely to benefit from informal lending or transfers, further reducing their options (Santos & Barrett 2011).

Veterinary services have been shown to be a highly effective means for reducing livestock mortality and for maintaining herd lactation rates (Homewood et al. 2006; Admassu et al. 2005; Sieff 1999). Since a large majority of household income is earned from milk production and livestock are the primary store of household wealth, this makes veterinary care a high-return investment. In Kenya, uptake of veterinary services is nonetheless low among pastoralists. Households report that access to providers, price, access to cash, and poor knowledge of veterinary services play a large role in determining use (Heffernan 2001).

Most pastoralists sell livestock to buy grains or goods (Hogg 1997). Selling most often occurs when households need access to cash, not when prices are high (Barrett, Bellemare & Osterloh 2006), although households with larger herds tend to sell more actively (Bellemare & Barrett 2004; Lybbert et al. 2004; Vincent et al. 2010). In an analysis of pastoralists' market responses to price, Barrett et al. (2006, p.9) provide the insight, "[t]he idea that pastoralists will cash out animals in response to higher prices depends fundamentally on the assumption that there exists an alternative means by which to store wealth." Even where there is access to other financial assets, herders do not necessarily view them as lower risk that livestock (McPeak 2005).

Livestock markets in arid and semi-arid regions suffer from both supply and price variability. During droughts, access to rangeland water and feed falls, reducing the both the health of the livestock and the production of animal products on which households depend. These environmental factors may compel households to sell animals, both to meet the deficit left by a loss in livestock byproducts (Coppock 1994) and to avoid loss due to mortality (Holtzman & Kulibaba 1994). Since climatic shocks, such as drought, often take place over large regions, many households suffer the same drought and respond in a similar manner. The associated sudden increase in livestock supply causes prices to fall sharply, especially where markets are isolated (Barrett et al. 2003). In addition, periods of drought are also associated with increases in demand for cereals and grains, further reducing the terms of trade between livestock and other consumption goods (Holtzman & Kulibaba 1994). Post drought, herders who could benefit by using markets to help rebuild their herds face low supply, high prices and limited liquidity with which to restock commercially. Thus, depending on a number of market and environmental factors, households may find it beneficial to increase sales during drought (income smoothing) or reduce sales during droughts (asset smoothing). The empirical evidence from ASAL Africa points towards asset smoothing behaviors dominating (Fafchamps et al. 1998; McPeak 2004; Barrett et al. 2006; Carter & Lybbert 2012).

In summary, in northern Kenya successful pastoralists maintain herds large enough to maintain mobility, even over drought years with high mortality, but also diversify their income to include cash income generated from other non-pastoralist activities. The use of veterinary services is limited but high return, especially for maintaining herds' lactation rates on which current income heavily depends. Households that fall below a herd size mobility threshold are likely to struggle for a host of reasons associated with inability to effectively draw on the scares resources of the environment.

***Hunger Safety Net Program (HSNP)***

Phase I of HSNP in Kenya provided long-term, unconditional, scheduled cash transfers to 69,000 households in the four poorest districts of Kenya: Marsabit, Mandera, Turkana, and Wajir. Phase I was rolled out across communities starting in April 2009 and continued through the duration of this study, ending in June 2013.[73] Participating households were to receive Ksh 2,150 (about $26 US) every 2 months for a period of 2 years.[74] Payments were planned to take place in about 200 of 434 total sublocations in the four districts.[75] The program aims to target 40-50% of the population in each of the sublocations.

The objective of Phase I was to reduce food insecurity in those households that received transfers, evaluate the effectiveness of the program, and to evaluate three different targeting mechanisms that were used to determine which households received transfers. To that end, Phase I was implemented using an experimental quantitative survey design. The first phase was implemented by randomly designating 24 sublocations 'treatment' sublocations from a pool of 48 selected sublocations. Those treatment sublocations received transfers during the first two years of the program while the remaining 24 'control' sublocations received payments only during the final two years, as HSNP began to scale. Each treatment sublocation was also randomly assigned one of the following targeting mechanisms to determine who within each location was eligible for cash payment.

1. **Social pension**: All members in the community over the age of 54 receive payments. Households receive a transfer for each eligible member.
2. **Dependency ratio**: All households in which a certain percentage of the members are older than 55, younger than 18, disabled or chronically ill are eligible.[76]

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[73] Phase II of the program began in 2013. For more details, see http://www.hsnp.or.ke/.

[74] In 2009, Ksh 2,150 was greater than 50% of monthly household consumption for about 32% of the households whose data are used in this paper. The transfers were increased to 3,000Ksh in September 2011 and then to 3,500 Ksh in March 2012 due to drought and inflation.

[75] A sublocation was the smallest administrative jurisdiction in Kenya, followed by location, division, district and province.

[76] The initial HSNP literature stated that in communities using dependency ratio targeting, households in which 57% of the members are older than 55, younger than 14, disabled or chronically ill are eligible. We use a more recent definition that was also used in the HSNP impact evaluation (Hurrell & Sabates-Wheeler 2013). We retain the 57% threshold since no information on the threshold is provided in the more recent HSNP literature.

3. **Community based targeting**: The community is instructed to select those households that are most food insecure. Up to half of the community's households are to be selected this way.

Only a single targeting mechanism was used in each community. Once a household was selected to receive benefits, it received transfers for the entire period unless the beneficiary chose to drop out of the program, died, or moved out of the area. Importantly, households did not graduate and there was no retargeting process in the community.[77] Attrition is minor and analyzed in detail in Appendix A.

***Index based Livestock Insurance (IBLI)***

The IBLI product uses an index of predicted livestock mortality rates developed by a team of researchers from Cornell University, the University of California at Davis, and the International Livestock Research Institute (ILRI), as described in Chantarat et al. (2013). The team used historic, remotely sensed, Normalized Difference Vegetation Index (NDVI) observations and livestock mortality rates to develop a response function that predicts livestock mortality rate from various transforms of NDVI. NDVI is a model index signal as it is exogenous to individual actions, available freely, provides frequent observations in near real time, and has more than 20 years of archived data with which to estimate the response function and simulate the underlying distributions needed for pricing an insurance product.

Marsabit district was divided into five insurance divisions that correspond to established and commonly recognized administration boundaries, so as to reduce the likelihood of consumer confusion (Figure 1). A separate index is calculated in each insurance division corresponding to its area average NDVI values. If the division index predicts livestock mortality rates greater than the 15% contractual strike rate, then households receive indemnity payments equal to the product of the value of livestock insured and predicted livestock mortality rate less the strike. So the strike rates functions like a deductible in conventional

[77] For further information on the targeting and selection process of HSNP, see Hurrell et al. (2008).

insurance and IBLI provides insurance against the catastrophic loss layer of livestock mortality risk.

IBLI sales windows occur in the two months preceding each of the semi-annual rainy seasons. Policies are purchased in tropical livestock units (TLUs), which converts different types of livestock—goats, sheep, cattle, and camels, in this case—into a common unit based on metabolic weight.[78] Although there are two sales windows every year, an insurance policy provides coverage for 12 months so that policies may overlap or accumulate. Figure 2 illustrates the IBLI calendar.

Two private local insurance underwriters, APA and UAP, have commercialized and sold IBLI through local informants and sales agents. The underwriters choose to aggregate the five index divisions into two premium regions. The upper premium region is comprised of North Horr and Maikona while Marsabit, Laisamis and Loiyangalani make up the lower premium region.

Pilot grant funding provides field support for commercialization, transportation for sales agents, and direct premium subsidies. The subsidies come in two forms: This first is a universal reduction in the insurers' loaded premium rate. In the upper premium region, where the market price consumers faced was 5.5% of the value of insured livestock, the actuarially fair premium stood at 4.75% and the policy rate, including commercial loadings, taxes and other fees stood at 9.2% so that the effective premium subsidy was 67%. Similarly, pastoralists in the lower premium region faced a market price of 3.25% of the value of insured livestock, while the actuarially fair rate was 2.2% and the policy rate was 5.4%. Clients in the lower region thus benefited from an effective premium subsidy of 66%. This subsidy has remained constant since IBLI's January 2010 début through the period examine in this research, but has since changed.

[78] 1 TLU = 1 cattle = 0.7 camels = 10 goats or sheep.

The second subsidy is provided through a series of randomized discount coupons that are distributed before each sales season to participants in the household survey launched in order to evaluate the impact of IBLI (on which, more in section 4). The non-transferrable coupons are distributed to about 550 households semi-annually and provide a premium discount of between 10% and 60% for up to 15 TLUs of coverage per household.

Demand for IBLI has been comparable to or greater than that found in other studies of index insurance in developing countries, with 43% of surveyed households purchasing IBLI at some point over the period of study.[79] Over the four sales windows included in this research, about 3,300 policies have been sold for a total insured value of about USD 1.4 million. Severe drought conditions triggered indemnity payments to policy holders in all five insurance divisions in October-November 2011 and again in two of the five divisions during in March-April 2012, within our survey period.

## Data

This analysis uses household panel data from the Marsabit region collected under the Index Based Livestock Insurance (IBLI) project led by ILRI. The data were collected in four rounds. The baseline was collected in October-November 2009, one to two months before the IBLI pilot was announced and the product became available in January of 2010. Since then, three annual follow-up rounds have been collected each October-November.

The IBLI survey sites were selected according to specific parameters set to help learn about IBLI and how

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[79] Uptake among studied households (e.g., surveyed, provided with additional education, included in price incentive experiments) at actuarially fair premiums is commonly less than 20% and often much below that (e.g., Giné, Townsend & Vickery 2008; Karlan, et al. 2013; Mobarak & Rosenzweig 2012). At highly subsidized rates, uptake generally increases but is much below 100% even when the expected indemnity payments are much greater than the premium rate. Among the general population (non-studied households) uptake is usually negligible.

HSNP transfers interact with IBLI. Sixteen communities were randomly selected to represent the wide range of ecological and market conditions found in the Marsabit region and stratified to ensure that both HSNP targeted and non-targeted communities were included. Proportional household sampling was done at the community level. Within communities, households were selected by stratified random sampling using three wealth groups based on livestock holdings. For more information on survey design see ILRI (2012).

The survey tool included a wide variety of questions on household's demographic and economic characteristics. It emphasizes livestock related data, such as herd composition and detailed monthly livestock intake and offtake.

***Attrition***

A total of 924 households were surveyed in each round with attrition rates less than 4% between rounds. All exited households were replaced so that the sample size is 924 in all rounds. Whenever possible, exited households were replaced with households in the same community and wealth stratum. In some cases that was not possible due to availability constraints. In those cases, a household from a neighboring wealth stratum was chosen.[80] Households that left the survey have smaller families as measured by adult equivalent (AE), spend more on livestock, keep a smaller portion of their livestock at home, suffer fewer livestock losses, consume more per adult equivalent (AE), depend less on food aid, and have children who miss fewer days of school (see Table A1, Appendix A for more details). In many cases, the statistically significant differences arise in variables that we use as dependent variables, as outcomes of IBLI purchases and HSNP participation. As a precaution against attrition bias in our estimates, we reweight our observations using an inverse weighting procedure (Baulch & Quisumbing 2011; Fitzgerald, Gottschalk & Moffitt 1988; Wooldridge 2002). This process requires that the baseline data are observed, so we restrict analysis to

[80] The cases of out-of-stratum replacement most often involved replacing the individuals from the higher wealth group with those from a lower wealth group, which could explain the significant differences between exit, remaining, and replacement households. This is especially true after large-scale losses occurred in 2011.

households that participated in the baseline survey. For more details on the procedure used, see Appendix A.

### *Selection into HSNP Participation*

HSNP payments started in April 2009, about six months before the first round of the IBLI household survey. By the time that the first round of the IBLI survey was collected, 154 households in 5 of 16 survey communities had received benefits. The HSNP rollout added 120 participating households in 3 communities between 2009/2010 survey rounds, 80 households in 1 community between 2010/2011 rounds, and 10 households between 2011/2012 survey rounds (Table 1).[81] Although the survey data are collected annually, the HSNP implementing agent provided data on initial transfer dates for each community so that we can accurately estimate the number of payments that a household has received in each season.

There are a few abnormalities worth noting in the transitions described by Table 1. First, although transfers were originally meant to last for only two years, there is no obvious cessation in transfers, even in the cohort that started receiving transfers in April 2009. According to HSNP documentation, the transfers were extended past their original mandate of two years due to the 2011 drought. It is our understanding that the project continued to make transfers to all participating households that have not opted out or lost eligibility during the entire period examined in this research (2009-2012).[82]

In addition, some households report transfers in one period but then report no transfers in a following period (as reflected in non-constant diagonal values among participants in Table 1). There are 56 households that appear to stop participating in the program over the four survey rounds. The survey data indicate that, of

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[81] To examine the rollout progression and adherence to selection criteria of HNSP among the survey population, we restrict the data to the balanced panel (N=832), so that we have data on household characteristics during targeting and when each household began receiving transfers.

[82] According the program design, the only way to lose benefits is to opt out, to move out of the community, or for the recipient to die.

the 56 who stopped receiving transfers between surveys, one moved, four died, and it is unclear why the remaining 51 no longer receive transfers; they may have opted out. An additional 22 households report not participating in HSNP during at least one year between years that they report participating.

One additional peculiarity (not expressed in Table 1) is that in some cases, households outside of HSNP target communities report receiving HSNP transfers. In all cases, we use the household's reported participation, even when those reports do not coincide with the HSNP targeting or rollout parameters. We remain agnostic about the veracity of these discrepancies but potential causes, in addition to prospective measurement error, include unobserved household structures (e.g., households spread across multiple communities), migration (e.g., household moves out of HSNP target community but does not report the move to HSNP), or intra-household dynamics (e.g., changes to survey respondent's knowledge of transfers received by household member).

Each treatment community was assigned a single, known targeting scheme: pension, dependency ratio, or community designation.[83] If targeting is perfect, transfers are independent of household characteristics conditional on those characteristics associated with targeting and location. The four year weighted average adherence to selection is 85.2% among the general population and 70.0% among households within target communities while transfers were taking place. Accuracy was greatest in the age based targeting. A detailed analysis of the accuracy of each targeting scheme is found in Appendix B.[84]

From the perspective of the impact evaluation that follows below, the key point is that HSNP cash transfers

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[83] The targeting criteria for each target community were drawn from reports published on the HSNP website (http://www.hsnp.or.ke/) and meeting notes acquired by the authors. Those criteria were then corroborated by implementing personnel in Marsabit in August, 2012.

[84] Community based eligibility is estimated by regressing HSNP participation onto a set of target household characteristics described in the HSNP M&E strategy (Hurrell et al. 2008) within community designation communities. The parameter estimates from that initial regression are then used to generate propensity to participate scores and those with an estimated propensity of greater than 50% are categorized as eligible. See Appendix B for a full description of this process.

were expressly targeted based on observables, using a known set of community-specific criteria determined outside of the survey communities and assigned to specific communities randomly. Even though adherence to the criteria is imperfect in the survey data, the strong match between the exogenously specified selection criteria and self-reported receipt of cash transfers under HSNP enables us to instrument for HSNP participation using the known, exogenous selection criteria in order to produce clean estimates of the causal impact of HSNP receipt on various behavioral and welfare outcome variables of interest.

***IBLI Uptake and Indemnity Payments***

IBLI first became available for purchase in January 2010. More than a quarter of surveyed households purchased IBLI during that first sales window. Uptake and average coverage levels fell in the following sales windows but a significant portion of the survey households continue to purchase IBLI coverage in every season that it was available (Table 2). 43% of surveyed household purchased IBLI in at least one round, for average coverage of 3.15 TLUs. There were no sales during the August-September 2010 or January-February 2012 sales windows due to logistical complications among the insurance providers.

Indemnity payments were made in all four survey divisions after the long rain/long dry season (LRLD) in 2011 season and in Laisamis and Central/Gadamoji divisions after the short rain/short dry season (SRSD) in 2011 (Table 3). As a reminder, policies last for 12 months so that households that purchased coverage in during either the January-February 2011 sales widow or the August-September 2011 sales windows received indemnity payments during the SRSD 2011 indemnity payments.

***Costs of program provision***

Phase one of the HSNP lasted from 2009 until June 2013. The HSNP website (http://www.hsnp.or.ke/) states that "[f]unding was provided by DFID and AusAID, to a total of GBP 40.5 million [KSH 4.70 billion at 2009 exchange rates]. The government's contribution during phase one was primarily in hosting the Secretariat, providing policy direction, and facilitating work on the ground". We cannot locate estimates of the costs of support provided by the Kenya government. Omitting (the likely non-trivial) administrative and facilitation costs borne by the government, the total costs of providing transfers to 69,000 households was about KSH 68,100 per participant household.[85] These costs are prorated to reflect the period used in this analysis, which ends in March 2012. By March 2012 the program had provided transfers to 57,811 households and spent a total of KSH 2.7 billion.[86] The total prorated program cost per participating household was KSH 47,600.

The IBLI pilot in Kenya was funded through grants from DFID, USAID, AusAID, EU, World Bank, and the Global Index Insurance Facility (http://livestockinsurance.wordpress.com/ibli-kenya/). The total program costs for the four years of operation are estimated to be about KSH 99 million.[87] Of that, a fairly large portion went to the initial product development and continues to be used for evaluation research led by ILRI. Importantly, some of the ongoing overhead costs of the program are borne by the insurance providers who offer the product commercially.[88] By the final sales round considered in this data (August/September 2012) there had been 3,297 contracts sold, which is an average cost of KSH 30,000 per contract. The average number of contracts purchased by those that purchased IBLI in the survey data was 1.44, so that the average total program costs per client in the survey is estimated to be KSH 43,200.

The total program costs per participant is one metric for examining program cost but has some drawbacks, such as placing no value on externalities such as infrastructure support or research, and represents an upper limit for the cost per client because it includes fixed costs and thus may inflate average costs for pilot

[85] The number of participants (69,000) is drawn from the HSNP website http://www.hsnp.or.ke/.
[86] Figure from internal HNSP documents. The authors prorated the 2011/2012 budget to reflect only 8 months (July-February) of the July 2011-June 2012 budget cycle.
[87] Andrew Mude, the IBLI project leader, estimates that the four year (2009-2012) costs were USD 1.3 million, which is equal to KSH 99 million using the 2009 average exchange rate of USD 1=KSH 74.74
[88] Andrew Mude, the IBLI project leader, estimates that the insurance companies currently contributes 5-20% of program costs.

programs intentionally run at suboptimal scale during a trial period. In addition, both programs continued beyond the period examined by this research so that our estimates of total program costs per participant, which rely partially on budgeted items rather than expenses, include funds that may not have been spent by the final period of the data.

The marginal cost of an additional client offers an alternative cost metric, but necessarily omits the program's fixed costs and thus provides a lower bound estimate. The marginal cost of an additional HSNP participant is the sum of transfers that the participant receives. By the final season used in this analysis, the average HSNP participant had received 14.1 transfers with a total real value (2009) of KSH 32,150.

For IBLI, the marginal cost of an additional client is total subsidies captured by that client. As mentioned above, donors continue to provide a fixed premium subsidy on all purchases and a variable subsidy provided through the discount coupons distributed to 60% of the survey households by the research team. The average household that had ever purchased IBLI coverage had purchased coverage on a total of 3.03 TLUs during the sales seasons included in this analysis. They had done so receiving the fixed subsidy on all purchases and an additional discount provided by the discount coupon that averaged 29.8%. Accounting for variation in premium values between division and inflation, the average purchaser had captured about KSH 1,450 in premium subsidies by the final survey period.[89]

## Variables of Interest and Econometric Strategy

This research aims to investigate what, if any, impacts IBLI coverage and HSNP transfers have had on the behaviors and welfare of pastoralist households. To that end, we use a number of different household indicators as dependent variables. In the following discussion, we refer to those as outcome variables and

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[89] Figures are in real 2009 Kenya Shillings.

symbolically represent them by $y_{i,t}$ for outcome *y* for individual *i* in season *t*.

We use four variables of interest (VOI) to estimate the impacts of program participation: a dummy variable indicating that the household is a current HSNP participant ($HSNP_{it}$), current IBLI coverage ($IBLI_{it}$) in TLUs, lagged cumulative seasons as an HSNP participant ($HSNPC_{it} = \sum_{s=1}^{t-1} HSNP_{is}$), and lagged cumulative seasons with IBLI coverage ($IBLIC_{it} = \sum_{s=1}^{t-1} IBLI_{is}$). Current HSNP participation and IBLI coverage are intended to capture behavioral changes associated with changes to risk exposure due to assured HSNP transfers or IBLI coverage as well as the income effects of paying the premium and/or receiving transfers in that period. Total periods of HSNP participation and/or IBLI coverage provide a measure of the cumulative financial and behavioral effects on household outcomes. The two cumulative variables are lagged by one season so that the current season is not double counted.

Our initial analysis begins by examining each of the programs separately. The reduced form model is described in equation (1) where $VOI_{it}$ is a matrix of the two HSNP or IBLI program variables of interest, $x_{it}$ is a vector of household characteristics, $c_i$ is the household's time invariant fixed effect, and $\varepsilon_{it}$ is random error.

(1)
$$y_{it} = \beta_0 + \beta_1 VOI_{it} + x_{it}'\beta_2 + c_i + \varepsilon_{it}$$
$$VOI_{it} = \{(HSNP_{it}, HSNPC_{it}), (IBLI_{it}, IBLIC_{it})\}$$

All four variables of interest are almost surely endogenous to both observed and unobserved household characteristics. Explicitly, the impact of having livestock insurance is likely to be correlated with unobserved variables that are also related to the outcome variables; for example, those who choose to purchase IBLI are also likely those who benefit the most from livestock insurance.[90] Participation in HSNP is expressly non-random, targeted toward specific households. Although we can control for the targeting characteristics and eligibility thresholds, Section 4 provides evidence that selection criteria are unable to account entirely for the participation so that even after controlling for targeting variables and eligibility criteria our estimates are likely to be endogenous.

We use an instrument variables approach to identify the local average treatment effect (LATE) of our four variables of interest. The remainder of this section describes those instrumental variables.

***HSNP***

HSNP is a targeted cash transfer program. Because selection into the HSNP program is not random and the targeting criteria may be correlated with the outcome variables of interest, the regression model must include controls for the selection criteria. Furthermore there are households who receive transfers but do not meet the targeting criteria. An analysis of adherence to selection indicates that about 30% of participating households did not meet the selection criteria (Appendix B). Thus, we must allow for the possibility that households might have manipulated their eligibility in unobserved ways. If such non-compliance or misreporting is associated with characteristics that impact both HSNP participation and outcome variables, participation is endogenous to our outcome variables.

Toward that end, we can use an intent-to-treat estimator based on known, exogenous HSNP participation criteria. The intended eligibility is determined relative to a pre-specified, exogenous threshold in a continuous selection variable, either dependency ratio, age, or community selected need, depending on the

[90] This argument assumes that the purchaser has a good grasp of the product and her/his own expected outcomes. But selection issues remain even if that is not the case. So long as there exist unobservable characteristics that are correlated with both the outcome of interest and the IBLI purchase decision, the impact estimates will likely be biased.

criterion randomly assigned to the community. Because the eligibility threshold in each targeting dimension is exogenous, they provide variation in participation that can be used to identify the impacts of participation. This research exploits those exogenous thresholds as instrumental variables to estimate the impact of transfers in an environment of both imperfect selection and potential endogeneity of participation. Identification rests on the independence of the selection criteria thresholds from the outcome variables and a discrete increase in participation across the eligibility thresholds. This intent-to-treat instrumental variable correctly predicts participation in 70% of the survey observations (Appendix B), while controlling for the eligibility dimension in the primary estimation.

Appendix C examines the distribution of household attributes for distortions along the eligibility dimensions that might indicate systematic misreporting of household characteristics in order to meet the eligibility criteria, which would weaken our argument that the thresholds are exogenous. We find no evidence of such behavior. We also make sure to include flexible controls for household characteristics along the eligibility criteria dimensions (maximum household age, dependency ratio, and community determined need) in the primary estimations in order to allow for heterogeneous relationships between the eligibility criteria dimensions and outcomes.[91]

Instrumenting for accumulated seasons as an HSNP participant follows directly from the above regression model; accumulated seasons living in a targeted community and meeting the eligibility criteria of that community are the instruments. This can be thought of as including the entire sequence of past HSNP participation, instrumented in the same manner as current participation, in the outcome equation. The difference is simply that the sequence is aggregated into a single cumulative participation value for each

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[91] For each eligibility criteria dimension we include the household's attribute raised to the first, second, and third power. This flexible functional form allows for a nonlinear relationship between the eligibility criteria dimensions and outcomes. In some cases, such higher order forms can lead to instability in the parameter estimates, but an analysis including only first order controls arrives at the same conclusions as those presented in the results section below.

period.

***IBLI***

Identification of the impacts of IBLI rests on exogenous variation in purchases associated with receiving a randomly distributed coupon that provided premium discounts for those that purchase IBLI.[92] The data support that the coupons are random and correlated with demand (Appendix D).

Current coverage is the result of purchases in either of the preceding two sales windows, which can be instrumented for by using the coupon status in each of those two periods. Note that survey households received new coupons (or no coupon) randomly each sales period and the coupons were non-transferable among households and across sales periods. Similar to cumulative HSNP transfers, cumulative IBLI coverage can be instrumented by a variable that captures the accumulated seasons that the household received a discount coupon. The IBLI instruments are examined Appendix D.

IBLI purchases also have a direct impact on expected income, which is equal to the difference between expect indemnity payments and premium payments made. If households purchase IBLI at a premium rate that is above the expected indemnity rate, their expected income is less than if they had not purchased IBLI. At below actuarially fair premium rates, IBLI purchases are associated with a de facto transfer to the household's expected income. Unlike HSNP transfers, which are more or less constant over the survey period, there is variation in the impact of IBLI purchases on expected income due to the distribution of

[92] The IBLI research design also included a randomized education component that has a positive and significant impact on demand (Jensen, Mude & Barrett 2014). Unfortunately, we cannot leverage the exogenous variation in demand associated with the education component in the main fixed effects estimates examined in this paper because there is no intertemporal variation in game participation. We do include participation in the educational game in a pooled IV analysis found in Appendix E, which is performed as a robustness check of the fixed effect estimates.

discount coupons and because the expectation is a function of the quantity of coverage purchased.[93] Controlling for this expected income effect of purchases would allow us to isolate the impact of the insurance coverage from the impact of the premium transactions. But to do so requires instrumenting for both the amount purchased and the expected income effect, which is a first order function of the purchase level. The high degree of collinearity between the two instrumented variables results in highly unstable parameter estimates, so we abandoned that approach. Thus, our analysis of the impacts of IBLI capture both the income effects of premium transactions that are not uniformly actuarially fair and the risk mitigating effects of insurance coverage. But, we expect the direct income effects of IBLI purchases to be very small as the average purchaser paid 70 KSH less than the actuarially fair premium rate, the maximum payment greater than the actuarially fair premium for the amount of coverage purchased was 2,982 KSH, and the largest de facto transfer to a purchaser was 4,898 KSH,[94] all for a 12 month contract. Although the largest de facto transfer is quite substantial, only 1.4% of IBLI purchases resulted in a de facto transfer larger that a single HSNP transfer. The average transfer is nearly zero, and 47% of purchase are made at a loaded premium rate, so that the net income effect is negative.

Our final analysis of both programs simultaneously uses an interaction between cumulative seasons of HSNP participation with cumulative seasons with IBLI coverage. The interaction is instrumented using interactions between the instrumental variables that are used for each separately.

Our statistical analysis uses data from all four rounds of the survey but does not include data from the SRSD 2012 season because the outcomes of interest are estimated at the end of each season, which is not captured

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[93] Although there are small changes to the consumer price index and in the transfer size itself, which could be used to separately identify the impacts of participation and the impact of the transfer size, practically speaking, the variation is too small for us to separately identify the two.

[94] The actuarially fair premium rates are below the premiums that pastoralists faced in the field without a discount coupon. For the period examined in this study, the actuarially fair premium rates were estimated to be 713 KSH and 330 KSH in Upper and Lower Marsabit regions, respectively.

for SRSD 2012 in our data. We present and discuss the results of fixed effects instrumented variables estimates in the main body of the paper. Pool instrumented variables estimates are included in Appendix E as a robustness check. A full description of included covariates and the outcome variables is found in Table 4 and summary statistics are included in Table 5.

## Results

This presentation and discussion provide results from the HSNP and IBLI regressions side by side. There are some differences between the two programs that will direct interpretation of parameter estimates. Very few HSNP participants stop participating in the program so that the HSNP variable is nearly always one when lagged cumulative transfers ($HSNPC_{it}$) are greater than zero. We can therefore gain insight into an HSNP participant's initial reaction and longer-term reactions to HSNP by adjusting $HSNPC_{it}$. The IBLI variables are not so closely linked. Nearly half of the households purchase IBLI at least once but very few purchase in every season so that IBLI is often zero when $IBLIC_{it}$ is greater than zero (59% of observations). In addition, we are also interested in the impact of the level of coverage so that the current coverage variable for IBLI is not a dummy variable as it was for HSNP. See table 6 for summary statistics of the HSNP and IBLI variables.

We begin by examining the impact of HSNP participation and IBLI coverage on pastoral production strategies. From previous studies, we expect that insurance coverage may increase investments in pastoral production among the risk constrained (Karlan et al. 2014; Mobarak & Rosenzweig 2012) and may change their coping strategies when droughts occur (Janzen & Carter 2013). Cash transfers have also been shown to impact risk taking and investments in productive capital (Bianchi & Bobba 2012; Covarrubias et al. 2012; Gertler et al. 2012; Stoeffler & Mills 2014) and an analyses of the HSNP by their external evaluators found qualitative evidence that transfers were associated with increased livestock retention (Hurrell & Sabates-Wheeler 2013).

Investments in production could take a number of forms including increased herd size, increased expenditures on veterinary services to safeguard and improve the productivity of one's pre-existing herd, or changing herding strategies. We therefore estimate the impact that IBLI coverage has on: herd size, expenditures for vaccines and veterinary care to capture investments in existing productive capital, the ratio of animals kept at home (rather than in satellite camps) and the mobility status of the household to test for changes to herding strategies.[95]

HSNP participation increases the likelihood that households are partially or fully mobile (column 2, Table 6) and there is weak evidence that the effect accumulates over time so that longer-term participants are more likely to be partially or fully mobile than newer participants (column 1, Table 6).[96] These findings are *inconsistent* with those of Hurrell and Sabates-Wheeler (2013), who found that HSNP had no impact on mobility, but are encouraging in the Marsabit region where sedentarization and poverty often go hand in hand. In addition, there is evidence that as duration of HSNP participation increases, households enjoy increased milk production value per TLU and experience lower livestock mortality rates (column 1, Table 6).

Greater historic IBLI coverage leads to reduced herd sizes and increased expenditures on livestock veterinary services. These investments in existing productive capital bring significant increases in milk

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[95] Data on water, supplementary feed use, transaction costs, and other expenditures were also collected but are very sparse. In every case, except for veterinary services, the median and mode expenditures were zero. In addition, expenditures on veterinary services has the second highest mean, the lowest maximum and lowest standard deviation. Because our analysis inevitably examines variation around the average, we restrict our expenditures to veterinary services.

[96] A linear probability model is used to estimate the impact of IBLI coverage on the partially or fully mobile binary variable.

productivity (column 3, Table 6).[97] Current depth of coverage has similar impacts on veterinary and milk related variables; increasing investments in animal health and increasing value of production (column 4, Table6). In addition, households with current coverage maintain smaller portions of their herd at the household, an indication of greater mobility.

To examine coping strategies, we construct an indicator variable that equals one during seasons in which a division's average livestock mortality rate is equal to or above 15%. For both IBLI and HSNP, we estimate the impact that shocks, participation/coverage, and participation/purchase during shocks have on livestock sales. Historic participation/coverage is omitted from this analysis to focus on the impact of the impact of the household's current status.

Covariate shocks have a significant and positive impact on livestock sales (Table 7). There is no evidence that HSNP transfers or IBLI coverage change households' sales behavior during shock seasons.[98] There is strong evidence that households with insurance coverage sell more livestock than do those without insurance during seasons when livestock mortality is low, and thus when livestock prices are high, as discussed in section 2. These households are therefore timing sales more effectively to generate greater revenues and, presumably, profits.

There is a danger that these results are, in part, due to certain types of households facing many or severe

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[97] As a means of connecting IBLIs impact on livestock health services and milk production, we regress milk production (L/TLU/day) onto household covariates and livestock health expenditures (KSH/TLU) and household fixed effects. We find that increased expenditures are positively and significantly related to increased milk production (Coef. Est. = 0.0593, Std. Err.= 0.0096). This analysis is not included in this paper.

[98] To determine the impact of insurance on livestock sales during shock years, we test if the sum of estimated parameters for current coverage and current coverage during shock years is significantly different than zero (row 4, Table7).

idiosyncratic shocks. Notice that the results in Table 6 indicate that the HSNP estimates may suffer from endogeneity, as HSNP households with a long history of HSNP participation suffer lower livestock mortality rates and thus few shocks. To test the robustness of our findings, we re-estimate Table 7, with an individual measure of shock. These estimates are found in Table G1, Appendix G. The findings are consistent with those that use the covariate definition of shocks; HSNP participant households sell livestock in greater numbers during shock years (although statistical significance is lost in the HSNP analysis), neither HSNP participation nor IBLI coverage impacts livestock sales during shocks, and those households with IBLI coverage sell more livestock during non-shock seasons.

One potential explanation for increased market participation among the insured during non-shock seasons is that households with insurance are more willing to respond to the threat of drought, increasing sales in anticipation of drought or as the result of past droughts. This possibility is tested by examining household response to past and coming covariate shocks. Once again, the main impact of IBLI seems to be that it allows households to increase livestock sales in seasons that are not considered shocks (Table G2, Appendix G).

There are a number of reasonable explanations for increased livestock sales with insurance coverage. Increased livestock sales associated with insurance coverage may be the result of reduced precautionary savings as predicted by Ikegami, Barrett & Chantarat (2012) and hinted at in the reduced herd size among those with a history of IBLI coverage. Alternatively, it could be that premium payments necessitate livestock sales outside of shock periods, when animals fetch higher prices (Barrett et al. 2003), as pastoralists typically hold little cash savings. Finally, households may use the insurance as a calculated gamble, buying insurance and selling their livestock before periods that they believe will trigger the index, effectively shorting the livestock market. But if this final explanation were true and households were successfully predicting shocks, the impact of coverage on livestock sales before a shock would be positive, which it is not (Table G2). Thus we are left with the possibility that households respond to reduced uninsured risk exposure by drawing down precautionary savings, that IBLI coverage increases livestock sales due to the need to raise cash to pay premiums, or that they unsuccessfully use IBLI as a lottery. In light of increased expenditures on livestock health care and increased milk income, a reduction in precautionary savings is the most credible explanation of observed patterns.

We now examine the impacts that each of these programs has on welfare. To do so, we construct a set of welfare indicators similar to those that are often examined by cash transfer programs. We use three indicators of household welfare (consumption per adult equivalent, an asset index, and monthly income) and four indicators of investments in children's human capital (ratio of school aged children enrolled in school, student absentee days, weight for height z score, and mid-upper arm circumference [MUAC]).

HSNP participation has an initial positive impact on asset wealth but that effect falls away quickly in subsequent seasons (column 1 and 2, Table 8). Current IBLI coverage has a positive and significant impact on income per adult equivalent (column 2, Table 8). Most striking is the stark lack of consistently positive, statistically significant impacts from either program.

If there are no time invariant household fixed effects, the fixed effects model is inefficient. It is possible that those potential inefficiencies are obscuring significant impacts of program participation. As a robustness check, we re-estimate the analyses found in Tables 6-8 using a pooled instrumental variables model. This approach has that added benefit of tapping an additional instrumental variable for IBLI uptake: randomized participation in the educational game. The pooled estimates, found in Appendix E, confirm the general narrative of our primary analysis although statistical significance changes in a few cases. Most significantly, there are no great changes in the significance welfare outcomes.

Before comparing the effects of HSNP and IBLI jointly, we first establish that there is at least some overlap between the two programs.[99] Of the 576 observations of ILBI purchases, 194 (34%) take place in households receiving HSNP transfers. Although the overlap in clientele is not large, it is certainly feasible for 194 observations to provide statistical evidence of prospective interaction effects. In comparing the effects of HSNP and IBLI simultaneously on household welfare, we focus on the cumulative seasons with IBLI coverage and cumulative seasons receiving HSNP transfers. We also include an interaction between the two, in order to determine if any synergies appear between the two programs. There is no evidence that the two programs interact, nor do we reveal impacts in either that were not evident when they were analyzed separately (Table 9).

To compare the relative benefits of each program, we scale estimated benefits by each program's costs. We focus on the two production and welfare outcomes for which point estimates suggest welfare improvements under both programs: milk income and income per AE. The final average benefits in each of these dimensions are estimated using the average VOI values during the final period, for clients of each program. The average VOI values used to estimate final average benefits are provided in Table 10.

Before discussing the benefits normalized by costs, note that this analysis looks at the full public costs of HSNP and IBLI clients but only examines benefits along a few specific dimensions. This is not a comprehensive cost-benefit analysis, which would require that we observe and value all the benefits associated with each program. Rather, this analysis examines the benefits associated with two specific outcomes only, normalized by program costs in order to provide a basis for comparison.

The average benefits among those that ever participated in the HSNP program or ever purchased IBLI

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[99] It could easily be the case that there is very little overlap. As Binswanger-Mkhize (2012) points out, the poorest are unlikely to purchase insurance while HSNP explicitly targets the poorest.

coverage are estimated using the average VOI values mentioned above and the parameter estimates in Tables 6 and 8. Table 11 summarizes the average benefits estimates and the unit costs of those benefits. Normalizing by total program costs per client, the two program produce changes in outcomes that roughly the same in magnitude. But the marginal cost of an additional client is much smaller for IBLI than HSNP. Normalizing benefits by the marginal cost of an additional client, IBLI's benefits are much more cost efficient than HSNP's.

These estimates bracket the true costs per client and highlight the variation in program cost structures. Cash transfer programs, such as HSNP, have overhead costs that go towards the targeting process and administration of transfers but the good that they are providing—cash—comes at cost and providers often provide little other support. Alternatively, offering an index insurance pilot in a region without insurance requires generating a product and developing a market for it, all at high initial cost. The hope is that once public funds have overcome the largest fixed costs of product and markets have developed, private enterprises will enter and begin to shoulder some or all of the operating costs. That has been the experience of IBLI in the initial pilot phase.

Cash transfers and publically supported insurance programs are two very different approaches to providing social protection. This research finds evidence that both approaches can benefit clients, although their benefits may differ. HSNP targeting is intended to target and help the poorest households. In the northern Kenyan environment, where herd size, mobility, and poverty are tightly linked, HSNP transfers protect these poor households from livestock losses and help maintain mobility.

Any household with sufficient access to cash can purchase social insurance where it is available. Those that purchase IBLI, take advantage of their reduced exposure to risk by drawing down their herd size and increasing investments in the productivity of their livestock to increase milk production and income.

Although Jensen, Mude and Barrett (2014), find that HSNP participation impacts both likelihood of uptake and level of purchase conditional on uptake, such interactions do not produce statistically significant impacts on the welfare measures considered here.

Thus, determining which approach best fits the aims of a social protection program depends both on the intended clientele and on the program objectives. Cash transfers can be targeted to specific subpopulations and implemented with fairly low start-up costs. Although program size may reduce the per client burden of those initial investments, transfer programs will always face the substantial variable cost burden of the transfers themselves. By contrast, IBLI provides evidence that publically supported insurance can produce beneficial impacts on scale similar to those associated with HSNP transfers but with a very different cost structure. There are many up-front costs to developing a context-specific insurance policy, educating the public on the product, and marketing it. Such social insurance schemes run the risk that low uptake will result in few household benefiting from the large initial public investments. For IBLI, at pilot scale, the ratio of total program costs per client to marginal cost of an additional average client is extremely large, highlighting the heavy burden of fixed costs when the client pool is small. If the client pool for IBLI expands significantly, as the Government of Kenya proposes to do in taking IBLI nationwide in 2015, there is the potential for the total program costs per client to fall sharply due to the low marginal costs of subsidizing premiums.

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## Figures

**Figure 1.** Marsabit region with surveyed sublocations by HSNP and IBLI status

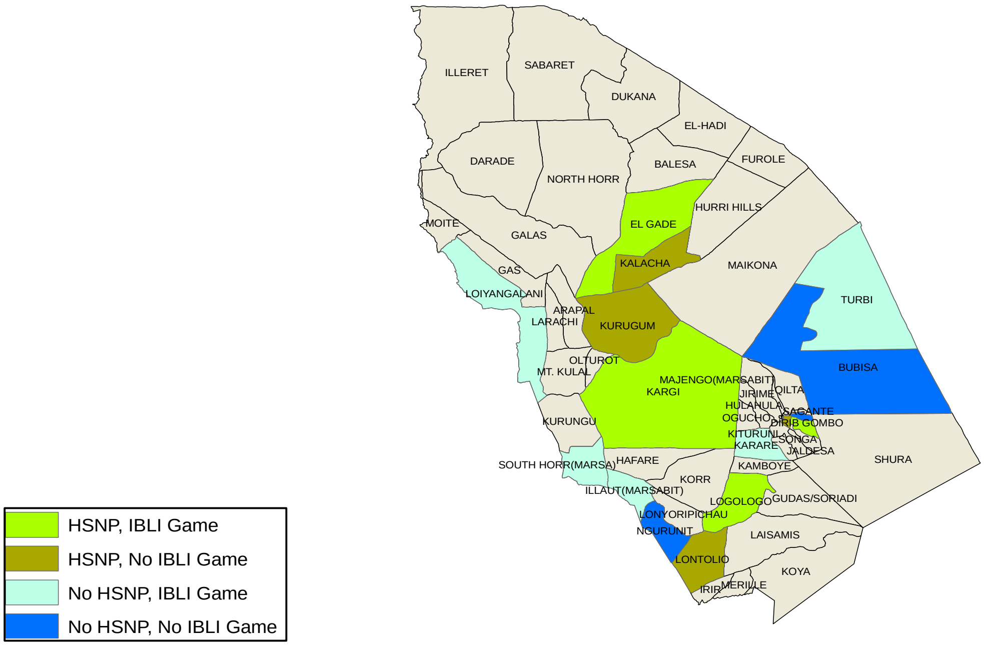
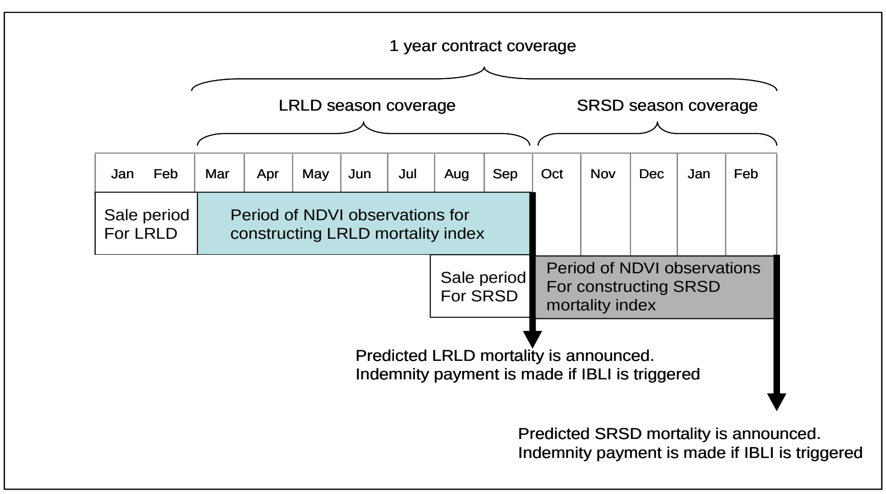



**Figure 2.** IBLI calendar



## Tables

**Table 1.** Rollout of HNSP across IBLI survey households in 2009-2012 survey rounds

| | Survey Year | | | |
|---|---|---|---|---|
| | 2009 | 2010 | 2011 | 2012 |
| Non-participants | 678 | 574 | 503 | 524 |
| 1st year of participation | 154 | 120 | 80 | 10 |
| 2nd year of participation | 0 | 138 | 113 | 62 |
| 3rd year of participation | 0 | 0 | 133 | 106 |
| 4th year of participation | 0 | 0 | 0 | 130 |
| Total[1] | 832 | 832 | 829 | 832 |

[1] Changes to total are due to missing participation data.

**Table 2.** IBLI uptake and demand conditional on purchase in the IBLI survey, Jan. 2010 – Nov. 2012

| | | Purchasing | Average purchased coverage (standard deviation) | | | |
|---|---|---|---|---|---|---|
| Year | Season | Households (N) | Central/Gadamoji | Laisamis | Loiyangalani | Maikona |
| 2010 | LRLD | 256 | 6.58 (7.65) | 3.37 (4.65) | 2.34 (2.19) | 2.75 (2.57) |
| | SRSD | - | | | | |
| 2011 | LRLD | 134 | 3.53 (2.93) | 2.57 (3.98) | 2.30 (2.79) | 4.15 (3.77) |
| | SRSD | 127 | 2.93 (3.06) | 1.74 (1.48) | 1.92 (1.53) | 4.18 (5.55) |
| 2012 | LRLD | - | | | | |
| | SRSD | 80 | 4.03 (3.57) | 1.43 (0.87) | 1.50 (0.95) | 3.49 (6.27) |

The total number of surveyed household in each round was 924. LRLD is the long rain/long dry season that lasts from March 1st through September 30th. SRSD is the short rain/short dry season that lasts from October 1st through February 28th.

**Table 3.** Index values and associated indemnity rates

| | Index = predicted mortality rate (indemnity rate) | | | |
|---|---|---|---|---|
| Season | Central/Gadamoji | Laisamis | Loiyangalani | Maikona |
| LRLD 2010 | 0.00 (0) | 0.02 (0) | 0.02 (0) | 0.01 (0) |
| SRSD 2010 | 0.06 (0) | 0.06 (0) | 0.06 (0) | 0.02 (0) |
| LRLD 2011 | 0.26 (0.11) | 0.22 (0.07) | 0.18 (0.03) | 0.33 (0.18) |
| SRSD 2011 | 0.23 (0.08) | 0.20 (0.05) | 0.12 (0) | 0.06 (0) |
| LRLD 2012 | 0.05 (0) | 0.02 (0) | 0.03 (0) | 0.02 (0) |

LRLD is the long rain/long dry season that lasts from March 1st through September 30th. SRSD is the short rain/short dry season that lasts from October 1st through February 28th.

**Table 4.** Description of key variables

| Household Attributes: | |
|---|---|
| Male | =1 if head of household is male. |
| Age of Head | Age of head of household, in years. |
| Head is Widow | =1 if head of household is a widow. |
| Education | Maximum education achieved by a household member, in years. 1-8 are standards, 9-12 are forms 1-4, diploma is 13, degree is 14, and postgraduate is 15. |
| Adult Equivalent | The sum of household members’ adult equivalence (AE) where AE is determined by the following: AE=0.5 if age<5, AE=0.7 if 4<age<16 or age>60, AE=1 if 15<age<61. |
| Dependency Ratio | The ratio of dependents to total household members. For consistency with the HSNP targeting criteria, we us the definition of dependents as those members that are under 18 or over 55 years old, chronically ill or have a disability (Hurrell & Sabates-Wheeler 2013). |
| Max Age | Age of oldest household member, in years |
| Community Based Need | The likelihood of HSNP participation generated using parameters estimated by regressing HSNP participation on a set of covariates for households in communities that used community based targeting, as described in Appendix B. The covariates used in that regression are described below. |
| Herd Size | Sum of livestock owned by the households where 1 TLU=0.7 camels=1 cattle=10 sheep=10 goats. |
| Expenditures on livestock | Total amount spend on vaccinations and other veterinary services in the last 12 months in real (February 2009) Kenya Shillings. |
| Ratio livestock held at home | The ratio of livestock that the household never moved to satellite camps in the last 12 months as a proportion of total herd size. |
| Mobile | A set of three mutually exclusive dummy variables indicating that the household is fully settled, partially settled, or nomadic. |
| Income from Milk | Value of seasonal average daily milk production in real (February 2009) Kenya Shillings. |
| TLU losses | Total number of livestock that died in that season (TLU). |
| Livestock Mortality Rate | Total number of livestock that died in that season divided by the total number of livestock owned in that season. |
| Livestock Sales | Livestock sold (TLU). |
| Consumption per AE | Value of monthly consumption per adult equivalent estimated using weekly recall of food purchases, one month recall of less frequent consumables purchases (e.g., charcoal, soap, transportation), three month recall of recreation and health related expenses, and 12 month recall of large purchases and durables (e.g., cloths, school fees, kitchen equipment). See the survey codebook for more details (IRLI 2012). |
| Asset Index | The asset index is generated using a factor analysis of household productive assets and other durables, primary cooking and lighting fuels, household construction materials, primary water source, and toilet facilities. The details of the factor analysis are found in Appendix F. |
| Income | Average monthly income in real (February 2009) Kenya Shillings. |

*Table 4 continues.*

*Table 4 continued.*

| | |
|---|---|
| Ratio Food from Aid | Total food aid as a share of total food consumption including food aid. |
| School Absenteeism | Number of days in the past 12 months that an enrolled student missed from school. |
| School Enrollment | Ratio of school aged children (ages 6-18) enrolled in school. |
| Child Attributes: | |
| Male | =1 if child is a male. |
| Age | Age of child in months. |
| Supplementary Food | =1 if child is receiving supplementary food. |
| Weight for Height Z-score | Weight for height Z-score calculated using STATA's user written command zscore06 (Leroy 2011) on survey measured weight and height. Z-scores are Winsorized at \|z-score\|>4. Of 2,402 observations, 44 observations had z-scores above 4 and 131 fell below -4. |
| MUAC | Survey measured mid-upper arm circumference. |
| Additional variables used to estimate community based HSNP eligibility. | |
| Aid | Average seasonal value of monthly food aid and employment programs from NGOs or the government in real (February 2009) Kenya Shillings. |
| CID | =1 if household has member that is chronically ill or disabled. |
| Savings | =1 if household has savings |
| IBLI Control Variables | |
| Index | Season's predicted livestock mortality rate based on the IBLI response function (index). |
| Coupon | =1 if household received a discount coupon. |
| | |
| Program Variables | |
| HSNP | =1 if household is an HSNP participant in the current season. |
| HSNPC | The total number of preceding seasons as an HSNP participant. |
| IBLI | Amount of current coverage in TLUs. |
| IBLIC | The cumulative preceding seasons with IBLI coverage. |

**Table 5.** Summary Statistics

| | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| Household Attributes: [A] | | | | |
| Male | 0.598 | 0.483 | 0 | 1 |
| Age of Head | 47.9 | 18.3 | 18 | 98 |
| Head is Widow | 0.147 | 0.354 | 0 | 1 |
| Education | 3.52 | 4.47 | 0 | 15 |
| Adult Equivalent | 4.72 | 2.04 | 0.7 | 14.8 |
| Dependency Ratio | 0.602 | 0.209 | 0 | 1 |
| Max Age | 46.4 | 16.2 | 19 | 106 |
| Community Based Need | 0.454 | 0.299 | 0.00 | 1.00 |
| Herd Size | 12.4 | 19.5 | 0 | 177 |
| Expenditures on livestock | 474 | 1,820 | 0 | 35,300 |
| Expenditures on livestock/TLU | 165 | 1,040 | 0 | 24,500 |
| Ratio livestock held at home | 0.343 | 0.375 | 0 | 1 |
| Mobile | 0.829 | 0.433 | 0 | 1 |
| Income from Milk | 336 | 1,630 | 0 | 18,400 |
| Milk Income per TLU | 30.9 | 336 | 0 | 8,490 |
| Milk Income per TLU \| >0 | 468 | 1,090 | 10 | 8,490 |
| TLU losses | 0.816 | 4.970 | 0 | 97.5 |
| Livestock Mortality Rate | 0.064 | 0.198 | 0 | 1 |
| Livestock Sales | 0.805 | 2.01 | 0 | 19.1 |
| Consumption per AE | 1,640 | 1,580 | 233 | 18,400 |
| Asset Index | -0.149 | 1.160 | -1.02 | 8.49 |
| Income | 3,910 | 12,100 | 0 | 225,000 |
| Ratio Food from Aid | 0.315 | 0.150 | 0 | 0.8 |
| School Absenteeism | 1.90 | 5.53 | 0 | 66 |
| School Enrollment | 0.535 | 0.409 | 0 | 1 |
| Child Attributes: [A] | | | | |
| Male | 0.532 | 0.500 | 0 | 1 |
| Age (months) | 37.4 | 13.3 | 11 | 60 |
| Supplementary Food | 0.412 | 0.493 | 0 | 1 |
| Weight for Height Z-score [B] | -0.677 | 1.52 | -4 | 4 |
| MUAC | 14.2 | 1.18 | 10.0 | 17.5 |
| Program Variables: [C] | | | | |
| HSNP Participant (HSNP) | 0.262 | 0.446 | 0 | 1 |
| Cumulative HSNP (HSNPC) [D] | 0.727 | 0.803 | 0 | 7 |
| HSNPC \| HSNPC>0 [D] | 3.05 | 3.21 | 1 | 7 |
| IBLI Coverage (IBLI) | 0.305 | 1.88 | 0 | 60 |
| IBLI \| IBLI>0 | 2.48 | 3.31 | 0.1 | 60 |
| Cumulative IBLI (IBLIC) [D] | 0.212 | 0.228 | 0 | 3 |
| IBLIC \| IBLIC>0 [D] | 1.12 | 0.445 | 1 | 3 |

See Table 6 for a description of each variable. [A]Summary statistics for household and child attributes are from the baseline survey. [B]Weight for height z-scores are Winsorized at ±4. [C]Summary statistics for the program variables are estimated using data from all four survey rounds. [D]Cumulative variables are lagged by a single season.

**Table 6.** Impact of current HSNP participation and IBLI coverage on production and investment

| | HSNP | | IBLI | |
|---|---|---|---|---|
| | **Previous Participation** | **Current Participation** | **Previous Coverage** | **Current Coverage (TLU)** |
| Production strategies: | | | | |
| Herd Size | -0.167<br>(0.453) | -3.216<br>(4.121)<br>[3.316] | -5.912**<br>(2.776) | 0.139<br>(0.662)<br>[2.162] |
| Veterinary Expenditures (KSH) | 11.06<br>(59.95) | 371.3<br>(316.4)<br>[13.04] | 955.3**<br>(462.2) | 5.039<br>(167.5)<br>[11.69] |
| Veterinary Expenditures/TLU (KSH) | 95.01<br>(67.04) | 53.32<br>(185.8)<br>[2.112] | 163.9<br>(351.1) | 88.65<br>(104.7)<br>[2.651] |
| Ratio of Herd Held at Home | 0.0126<br>(0.0185) | 0.106<br>(0.0965)<br>[3.207] | 0.169<br>(0.165) | -0.118*<br>(0.0711)<br>[4.485] |
| Household is Partially or Fully Mobile [A] | 0.0322<br>(0.0206) | 0.185**<br>(0.0855)<br>[15.56] | -0.0871<br>(0.147) | 0.0934<br>(0.0658)<br>[13.60] |
| Production outcomes: | | | | |
| Milk income (KSH) | 200.1<br>(320.8) | 905.8<br>(1,191)<br>[11.16] | 1,545<br>(1,128) | 1,421**<br>(706.7)<br>[10.32] |
| Milk income per TLU (KSH) | 74.08**<br>(30.47) | -103.1<br>(127.8)<br>[13.10] | 760.8***<br>(211.1) | 118.8**<br>(57.25)<br>[9.807] |
| Livestock losses | -0.0958<br>(0.186) | 0.890<br>(0.937)<br>[7.949] | -1.233<br>(0.775) | 0.216<br>(0.387)<br>[7.426] |
| Livestock Mortality Rate | -0.0260**<br>(0.0115) | 0.0556<br>(0.0348)<br>[22.32] | -0.00838<br>(0.0599) | -0.00280<br>(0.0161)<br>[22.48] |

Both models are estimated using household fixed effects and include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. [A]A linear probability model is used to estimate the likelihood that a household is partially or fully mobile. Clustered and robust standard errors in parentheses. Model F-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1.

**Table 7.** The impact of covariate shocks, HSNP participation, and IBLI coverage on livestock sales (TLUs)

| | **HSNP Participation (IV)** | **IBLI Coverage (IV)** |
|---|---|---|
| Shock | 0.261*** | 0.362*** |
| | (0.0867) | (0.0818) |
| Participation/Coverage (P/C) | 0.215 | 0.188** |
| | (0.166) | (0.0826) |
| P/C*Shock | 0.0163 | -0.215 |
| | (0.203) | (0.158) |
| | | |
| $H_0$: P/C + P/C *Shock=0 t-statistic | 1.118 | -0.200 |
| | | |
| Observations | 6,564 | 6,570 |
| Households | 897 | 897 |
| Model F-statistic | 4.993 | 5.054 |

The shock is an indicator that the division average livestock mortality rates in the current season are equal to or above 15%. Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 8.** Impact of IBLI coverage and indemnity payments on household welfare

| | HSNP | | IBLI | |
|---|---|---|---|---|
| | **Previous Participation** | **Current Participation** | **Previous Coverage** | **Current Coverage (TLU)** |
| Consumption per AE | -60.36* | -32.17 | 355.7 | -180.7 |
| | (34.01) | (372.9) | (150.7) | (150.7) |
| | | [15.67] | | [13.03] |
| Asset Index | -8.715*** | 16.98* | -16.13 | -6.077 |
| | (3.031) | (8.765) | (23.26) | (4.697) |
| | | [18.26] | | [21.04] |
| Income per AE | 0.595 | 374.5 | 132.9 | 420.7*** |
| | (41.35) | (293.5) | (304.1) | (150.2) |
| | | [17.99] | | [19.13] |
| School Absenteeism | -0.179 | 1.315 | 1.552 | 0.278 |
| | (0.214) | (1.705) | (2.144) | (0.423) |
| | | [6.916] | | [5.436] |
| School Enrollment | 0.0242 | -0.0392 | 0.0931 | 0.0629 |
| | (0.0244) | (0.0941) | (0.115) | (0.0501) |
| | | [4.077] | | [3.785] |
| WHZ | 0.0663 | -0.0702 | -1.061 | -0.0249 |
| | (0.198) | (0.983) | (1.318) | (0.321) |
| | | [1.487] | | [1.552] |
| MUAC | 0.0729 | 0.539 | -0.417 | -0.0185 |
| | (0.109) | (0.651) | (0.846) | (0.226) |
| | | [7.086] | | [6.504] |

Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered robust standard errors in parentheses. Model F-statistic in brackets. *** p<0.01, ** p<0.05, * p<0.1.

**Table 9.** The impact of accumulated HSNP transfers and IBLI indemnity payments on household welfare

| | **Accumulated HSNP Seasons** | **Accumulated IBLI Coverage Seasons** | **Interaction** |
|---|---|---|---|
| Consumption per AE | -33.83 | 353.9 | -38.55 |
| | (88.07) | (263.9) | (85.68) |
| | | | [12.13] |
| Asset Index | -0.0298 | -0.0169 | -0.0437 |
| | (0.0355) | (0.151) | (0.0500) |
| | | | [13.67] |
| Income per AE | 151.6 | 308.7 | -190.9 |
| | (95.88) | (341.2) | (139.2) |
| | | | [17.21] |
| School Absenteeism | 0.0303 | 2.195 | -0.208 |
| | (0.465) | (2.145) | (0.540) |
| | | | [5.389] |
| School Enrollment | 0.0440 | 0.172 | -0.0472 |
| | (0.0328) | (0.112) | (0.0306) |
| | | | [3.203] |
| WHZ | 0.417 | 0.738 | -0.413 |
| | (0.305) | (0.674) | (0.792) |
| | | | [0.983] |
| MUAC | 0.00338 | 0.592 | 0.647 |
| | (0.295) | (0.730) | (0.765) |
| | | | [3.320] |

Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 10.** Average value of each program variable during the final period of analysis among program clients

| VOI | Mean VOI in Final Period |
|---|---|
| HSNP [A] | 0.89 |
| HSNPC [B] | 3.85 |
| | |
| IBLI [C] | 0.45 |
| IBLIC [D] | 1.19 |

To determine the final impact of each program, we estimate the average values of each program variable in the final period and in each case, restricting the sample to those that had ever been a client of that program. [A] HSNP is equal to one if the household is an HSNP participant in the final season, conditional on ever participating. [B]HSNPC is the lagged average cumulative seasons as an HSNP participant by the final season, conditional on ever participating. [C] IBLI is equal to the amount of coverage in TLUs during the final season, conditional on purchasing IBLI at least once. [D] IBLIC is equal to the number of preceding seasons with IBLI coverage during the final season, conditional on purchasing IBLI at least once.

**Table 11.** Average benefits per unit cost by the final survey season

| | | | Income from Milk | | Income per AE | |
|---|---|---|---|---|---|---|
| Cost structure | | Cost | Impact | Impact/Cost | Impact | Impact/Cost |
| Total Program Cost/Participant | HSNP | 47,600 | 1,580 | 0.0331 | 336 | 0.0071 |
| | IBLI | 43,200 | 2,480 | 0.0574 | 347 | 0.0080 |
| | | | | | | |
| Marginal Cost of an Additional | HSNP | 32,150 | 1,580 | 0.0490 | 336 | 0.0104 |
| Participant | IBLI | 1,450 | 2,480 | 1.7090 | 347 | 0.2400 |

All values in real 2009 Kenya Shillings. Costs estimates are described in section 3. Impacts are estimated using the average values provided in Table 10 and parameter estimates in Table 6 and Table 8.

# Appendices

## *Appendix A: Analysis of Attrition*

We use 2009 data to compare the attrited households with the balanced panel. Those households that leave the survey have smaller families, spend more on livestock, keep a smaller portion of their livestock at home, suffer fewer livestock losses, consumer more per AE, depend less on food aid, and have children that miss fewer days of school.

**Table A1.** Summary statistics of the balanced panel and those that left the survey

| | Attrited Households | | Balanced Panel | | Difference | t-stat | |
|---|---|---|---|---|---|---|---|
| | Mean | St. Err. | Mean | St. Err. | | | |
| Household Attributes: | | | | | | | |
| Male | 0.59 | 0.09 | 0.60 | 0.04 | 0.01 | 0.14 | |
| Age of Head | 45.46 | 2.69 | 48.06 | 2.18 | 2.60 | 0.75 | |
| Head is Widow | 0.22 | 0.08 | 0.14 | 0.03 | -0.08 | -0.91 | |
| Education | 4.27 | 0.67 | 3.46 | 0.29 | -0.81 | -1.10 | |
| Adult Equivalent | 3.65 | 0.22 | 4.82 | 0.11 | 1.17 | 4.75 | *** |
| Dependency Ratio | 0.61 | 0.03 | 0.60 | 0.02 | -0.01 | -0.37 | |
| Max Age | 44.6 | 2.39 | 46.6 | 1.26 | 1.99 | 0.74 | |
| Community Based Need | 0.41 | 0.04 | 0.48 | 0.02 | 0.07 | 1.54 | |
| Herd Size | 11.14 | 3.10 | 12.63 | 1.07 | 1.48 | 0.45 | |
| Expenditures on livestock | 882 | 137 | 443 | 48 | -439 | -3.02 | *** |
| Per TLU Expenditures | 88.5 | 35.8 | 168.2 | 44.3 | 79.6 | 1.40 | |
| Ratio livestock held at home | 0.18 | 0.04 | 0.36 | 0.03 | 0.18 | 3.49 | *** |
| Mobile | 0.84 | 0.04 | 0.83 | 0.02 | -0.01 | -0.19 | |
| Income from Milk | 2,063 | 1,705 | 268 | 73 | -1,796 | -1.05 | |
| Income per TLU | 90.0 | 71.4 | 28.8 | 7.8 | -61.2 | -0.85 | |
| TLU losses | 0.22 | 0.10 | 0.88 | 0.14 | 0.66 | 3.86 | *** |
| Livestock Mortality Rate | 0.03 | 0.01 | 0.06 | 0.01 | 0.03 | 1.88 | * |
| Livestock Sales | 1.24 | 0.15 | 0.66 | 0.12 | -0.58 | -3.00 | *** |
| Consumption per AE | 2,268 | 259 | 1,594 | 89 | -674 | -2.46 | ** |
| Asset Index | -0.12 | 0.11 | -0.15 | 0.06 | -0.03 | -0.22 | |
| Income | 2,473 | 1,239 | 4,019 | 475 | 1,546 | 1.16 | |
| Ratio Food from Aid | 0.23 | 0.03 | 0.32 | 0.02 | 0.09 | 2.73 | ** |
| School Absenteeism | 0.76 | 0.40 | 1.98 | 0.33 | 1.21 | 2.33 | ** |
| School Enrollment | 0.61 | 0.07 | 0.53 | 0.04 | -0.09 | -1.02 | |
| Child Attributes | | | | | | | |
| Male | 0.33 | 0.10 | 0.48 | 0.06 | 0.15 | 1.34 | |
| Age (months) | 34.96 | 2.70 | 38.36 | 1.61 | 3.41 | 1.09 | |
| Supplementary Feed | 0.23 | 0.08 | 0.34 | 0.05 | 0.11 | 1.19 | |
| Weight for Height Z-score | -0.84 | 0.19 | -0.71 | 0.14 | 0.13 | 0.57 | |
| MUAC | 14.28 | 0.19 | 14.08 | 0.11 | -0.20 | -0.89 | |

See Table 4 for a full description of each variable.

Although 4% is an extremely low rate of attrition, the differences between the balanced panel and attrited households do raise a concern that our main analysis could suffer from attrition bias. As an initial test for attrition bias, we estimated the main estimates found in Tables 6-9 of this paper with the balanced and unbalanced panel. That analysis found some indication of bias in the estimates in about 10% of the cases. In response, we adjust our analysis for attrition using the inverse probability weights method developed by Fitzgerald et al. (1988). The basic idea is to re-weight observations so as to place more importance on those households that are similar to households that leave the survey. This approach assumes that attrition can, at least partially, be associated with certain observed characteristics.

The weights are generated by regressing survey participation onto a set of observables using a probit model, which is then used to predict participation. The procedure is then repeated with a subset of those variables included in the first iteration. The excluded variables in the second iteration should affect propensity of attrition and are presumed to be related to the density of the outcome variables of interest. Generally the excluded variables are variables that the researcher believes impacts both attrition and outcomes, but would not normally be included in the outcome analysis. Common examples include lagged outcome variables, village level attrition rates, and indicators of exogenous shocks.

Following Wooldridge (2002), we only include the households that are present in the first survey round, omitting households that enter the survey after the first round at together. Probit analyses are performed for each survey round by regressing households' survey participation status on baseline characteristics: age, education level of the head, widow status of the head, household dependency ratio, and adult equivalence. In addition, the first unrestricted regression includes village level attrition, previous season's covariate loss rate, and the ethnic group that the household belongs to. The model statistics for these analysis are provided in Table A2.

**Table A2.** Full and restricted probit regressions used to construct inverse weights

| Survey Round | Model Statistic | Unrestricted Probit | Restricted Probit |
|---|---|---|---|
| 2 | Wald $\chi^2$ | 75.02 | 14.27 |
| | P-value | 0.000 | 0.014 |
| | Pseudo $R^2$ | 0.231 | 0.137 |
| 3 | Wald $\chi^2$ | 105.86 | 16.68 |
| | P-value | 0.000 | 0.005 |
| | Pseudo $R^2$ | 0.236 | 0.104 |
| 4 | Wald $\chi^2$ | 59.60 | 19.48 |
| | P-value | 0.000 | 0.002 |
| | Pseudo $R^2$ | 0.197 | 0.103 |

The inverse probability weights are the ratio of the predicted probability of participation from the in the restricted model to that of the unrestricted model. The mean weight after the first round is 1.02 with a maximum of 1.75 and minimum of 0.79. These weights are used in all the analysis in this paper.

### *Appendix B: HSNP Adherence to Selection and Precision of Targeting*

This appendix provides a more detailed analysis of HSNP targeting. We first examine the adherence to selection by targeting criteria, finding that the program's exogenous selection criteria correctly predict HSNP participation in 70% of cases. Then we determine to what degree HSNP successfully targeted its general target population, "those households that are chronically food insecure" or "have low consumption expenditure and low asset holdings; and/or "[a]re already reliant on food aid" (Hurrell et al. 2008, p8). We find that HSNP does seem to target those households with fewer assets and lower consumption per AE.

### *Adherence to selection*

To examine adherence to selection criteria we focus only on the data from a single year: 2011. 2011 is ideal because by then all target communities had begun receiving transfers, so that comparisons are made across targeting criteria in the same period, all targeting in this sample takes place before the 2011 survey, and it avoids 2012, which seems to have the most abnormalities related to entrance and exit from the HSNP.

In pension communities, all individuals 55 years and older should have been eligible to receive HSNP transfers and no households without a member older than 54 should have received transfers. Households with more than one "pensioner" should have received payments for each, although we do not examine the data for compliance in that dimension.

In 2011, 79% of survey households in the pensioner-targeted communities of El Gade, Logo Logo, and Lontolio were correctly targeted (Table B.1). The inclusion error rate was 8% and the exclusion error rate is 13%. Meeting the targeting criteria (being above rather than under the target age of 55) increases the likelihood of receiving HSNP payments by about 46% in these communities.

**Table B1.** HSNP adherence to selection in pension communities El Gade, Logo Logo & Lontolio

| | Criteria | |
|---|---|---|
| HSNP | Age < 55 | Age ≥ 55 |
| Non-participant | 0.62 | 0.13 |
| Participant | 0.08 | 0.17 |

Within communities that were randomly selected for the dependency ratio targeting scheme, all households with a dependency ratio greater than 57% should be eligible to receive transfers (Hurrell et al.2008). Dependents include any household members under 18, over 55, disabled, or chronically ill (Hurrell & Sabates-Wheeler 2013). None of the dependency ratio targeted communities had begun receiving payments by the time of the 2009 IBLI survey. By the 2011 IBLI survey, 106 households in dependency ratio targeted communities were receiving transfers. Of those participants, 62% met the dependency ratio criteria. The average adherence to selection criteria across all categories is also 62%.

**Table B2.** HSNP adherence to selection in dependency ratio communities: Kagri and Kurkum

| | Criteria | |
|---|---|---|
| HSNP | Dep. Ratio < 0.57 | Dep. Ratio ≥ 0.57 |
| Non-participant | 0.09 | 0.05 |
| Participant | 0.33 | 0.53 |

Within community targeted locations, households judged most in need of transfers were collectively selected by the community. 50% of each community was to be targeted this way (Hurrell et al.2008). Because there is no single variable or criterion that determines eligibility, an analysis of selection adherence is not meaningful. Instead, we test the variables used as controls for selection by the evaluation organizations[100] for their power to predict which households are most likely to receive HSNP transfers. This exercise serves two purposes. First, it tests if there is a systematic process for determining who was selected by the community. Second, we can determine if the set of controls used by the evaluation organization can

[100] HSNP evaluation was contracted to Oxford Policy Management (OPM), working with the Institute of Development Studies (IDS) at the University of Sussex (UK).

be used to generate a community based need score that is appropriate as a statistical control in the impact evaluation.[101]

To test for the predictive power of the controls, HSNP participation was regressed onto a set of household characteristics using a probit regression in order to estimate the propensity of HSNP participation.[102] Those with a propensity score greater than 0.5 were categorized as community targeted households while those falling below that threshold were considered untargeted. This probit analysis is performed using data collected in October/November, 2009. At that time, three of four community based targeted communities had just begun receiving transfers (initial transfers in the three communities were made in April, June, and July). The fourth, Bubisa began in July 2011 but we use 2009 data for consistency and because there is no indication in the HSNP literature when targeting took place. This approach correctly predicts 65% of household participation in community based targeting communities (Table B.3).

**Table B3.** Community based targeting: Bubisa, Dakabaricha, Dirib Gombo & Kalacha

| | Criteria | |
|---|---|---|
| HSNP | Propensity Score < 0.50 | Propensity Score ≥ 0.50 |
| Non-participant | 0.31 | 0.28 |
| Participant | 0.07 | 0.34 |

The preceding analysis reveals that the systematic selection process outlined by the program strongly impacts who receives transfers. Within HSNP targeted communities, the average rate of adherence to selection criteria rate is 70%. But it is also clear from this analysis that the selection criteria are not the only factors that determine participation in the program. Therefore, our analysis proceeds with the assumption

101 The rationale for using OPM and IDS controls is our assumption that they had information on how the HSNP field workers guided the selection process and recorded trends in how the communities selected households.

102 Household level controls included: age of head of household, maximum age of household female head of household, widowed head of household, adult equivalents, dependency ratio, food aid, household type (fully settled, partially settled, nomadic), chronically ill or disabled members (dummy), savings (dummy), consumption per AE, proportion of consumption from food aid, asset index, and sublocation.

that observed HSNP participation depends as well on other, potentially endogenous, factors.

***Precision of Targeting***

The precision of targeting measures the program's record of providing transfers to the individuals that the program aims to assist. In this case, the target population consists of those households that are chronically food insecure or "have low consumption expenditure and low asset holdings; and/or [a]re already reliant on food aid" (Hurrell et al. 2008, p8). The precision of the HSNP program targeting is examined by individually regressing HSNP participation on the three criteria for chronically food insecure households specifically mentioned in the monitoring and evaluation strategy: total consumption per AE, proportion of consumption from food aid, and an index of asset holdings in the target communities.[103] Analysis is performed using data collected in 2009 to examine pre-transfer status.

Although the point estimates for the asset index and consumption per AE are in the expected direction, negative, increased percent from food aid seems to reduce the likelihood of HSNP participation (Column 1, Table B.4). The data used in this analysis were collected after the first transfers were made in 5 target communities.[104] Although it seems unlikely that the few pre-baseline transfers are driving the results, we perform a second analysis, restricting the data to those communities that had not yet received transfers at the survey baseline. In this restricted case, consumption per AE becomes more statistically significant, and the magnitudes of the point estimates on the asset index and consumption per AE increase (Column 2, Table B.4). Percent from food aid continues to be insignificant.[105] Thus it seems that the HSNP targeting is at least partially meeting it goal of targeting the food secure, although they are missing those households with

[103] See Appendix E for a full description of the asset index and its construction.
[104] Using target start dates for each community, we estimate that the following transfers had been made before our baseline data had been collected: 3 in Dakabaricha, 3 in Logo Logo, 2 in El Gade, 2 in Kalacha, 1 in Dirbi Gombo.
[105] As a point of interest, the correlation between the asset index and percent food from aid is -0.09, P-value=0.00, and between consumption per AE is -0.26, P-value 0.00, both in the expected direction if increased assets, reduced reliance on food aid, and increased consumption per AE are all indicators of food security.

a high percent of food from food aid.

**Table B4.** Probit regressions of HSNP participation on proxies of food insecurity

| | Average Marginal Effects | |
|---|---|---|
| **Proxies of Food Insecurity** | **Target Communities** | **Restricted Target Communities[1]** |
| Asset Index | -0.0939* | -0.251* |
| | (0.0505) | (0.130) |
| | [7.95] | [4.73] |
| Percent Food from Aid | -0.137 | -0.321 |
| | (0.306) | (0.412) |
| | [7.27] | [4.00] |
| Consumption per AE | -0.0172 | -0.0948* |
| | (0.0231) | (0.0491) |
| | [7.21] | [5.35] |
| Observations | 570 | 236 |

Community fixed effects included. 1The restricted sample excludes those communities in which HSNP transfers had commenced before the baseline data was collected: Dakabaricha, Logo Logo, El Gade, Kalacha, and Dirib Gombo. Standard errors in parentheses. Model F-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1

*Appendix C: Exogeneity of HSNP Instruments*

We use the variation in HSNP participation around the targeting criteria threshold to instrument for HSNP participation. For the thresholds to serve as valid instruments they must be exogenous and correctly identify an increase in participation. This appendix first examines household survey data to determine if there is evidence that households manipulate their reported structure (size, age, etc.) so as to fit the target criteria, which would endogenize satisfaction of eligibility criteria. We find no evidence of such manipulations. We then find that the targeting thresholds do identify a positive "jump" in the likelihood of HSNP participation, supporting their use as instruments.

Both analyses use a regression discontinuity design to test for a discontinuity in the probability density of responses for each of the criteria characteristics at the threshold. A discontinuity in the distribution of ages or dependency ratios at the threshold would suggest that households manipulated their self-reported characteristics to fit the criteria, calling into question the exogeneity of our instruments. Conversely, a lack of a discontinuity in the likelihood of HSNP participation at the eligibility thresholds would call into question the relevance of our instruments.

To test for discontinuities in either maximum age or dependency ratio data, we estimate the distribution of each variable by counting the number of observations for each reported age and each reported dependency ratio. We then regress that count onto an indicator of that the household meets the eligibility threshold, a third order polynomial of the running variable (age or dependency ratio), and a set of interactions of those polynomial terms with an eligibility threshold indicator variable. If households adjust their reported demographics to meet the HSNP eligibility criteria, we expect there to be a discontinuity in the number of households near the threshold. Such activity would be evident in significant parameter estimates for the threshold variables. We find no evidence that household responses to dependency ratio (Estimate= -1.564, Std. Err.= 5.447) or maximum household age (Estimate=1.218, Std. Err.= 1.307) are manipulated to meet the HSNP eligibility criteria during the targeting period in the targeted communities (Table C1.).[106]

**Table C1.** The observed probability distributions of reported age and dependency ratio (DR).

A. Distribution of reported maximum age

| | Likelihood of observed age |
|---|---|
| Threshold | 1.218 |
| | (1.307) |
| Age | 2.523* |
| | (1.351) |
| $Age^2$ | -6.656* |
| | (3.755) |
| $Age^3$ | 5.753* |
| | (3.363) |
| Threshold* Age | -6.310 |
| | (5.801) |
| Threshold* $Age^2$ | 11.844 |
| | (8.934) |
| Threshold* $Age^3$ | -8.113 |
| | (5.114) |
| Constant | -0.289* |
| | (0.156) |
| Observations[#] | 53 |
| $R^2$ | 0.288 |

Age is multiplied by 100 for convenient scaling.
[#] There are 53 unique reported maximum household ages in the three age-targeted communities at the time of targeting. Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

B. Distribution of reported DR

| | Likelihood of observed DR |
|---|---|
| Threshold | -1.564 |
| | (5.447) |
| DR | -0.733 |
| | (1.106) |
| $DR^2$ | 3.176 |
| | (4.788) |
| $DR^3$ | -3.103 |
| | (5.280) |
| Threshold* DR | 7.770 |
| | (21.026) |
| Threshold* $DR^2$ | -13.205 |
| | (27.015) |
| Threshold* $DR^3$ | 8.197 |
| | (11.69) |
| Constant | 7.669 |
| | (12.257) |
| Observations[#] | 23 |
| $R^2$ | 0.199 |

[#]There are 23 unique reported dependency ratios in the two dependency ratio targeted communities at the time of targeting. Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

The validity of the HSNP instruments also requires that the thresholds are correlated with participation. Household participation is regressed on a third order polynomial of the three targeting variables and the intent to treat indicator which is equal to one if the household lives in an HSNP target community and meets the targeting criteria of their community during the targeting period. The strength of the instrument rests on

[106] It is uninformative to perform a similar analysis on the estimated community score because that is smooth by construction (see Appendix B for details on the construction of the community score).

the statistical significance of the coefficient estimates associated with the IIT indicator and thus the variation in HSNP participation captured by the eligibility thresholds. The ITT coefficient estimate is positive and significant, confirming its relevance of the instrument (Table C2).

**Table C2.** The relationship between the intent to treat (ITT) indicator and HSNP participation

| | HSNP Participant |
|---|---|
| ITT | 0.614*** |
| | (0.050) |
| | |
| Observations | 7,036 |
| Pseudo $R^2$ | 0.524 |

Regression includes the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered and robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

*Appendix D: Appropriateness of IBLI Instruments*

For the coupons to be valid instruments they must be random and correlated with purchases. Table D1 provides a balancing test of key variables between those respondents who received coupons and those who did not. The balancing test is performed on the data from the season immediately preceding each coupon distribution, so that the data do not capture households' responses to receiving a coupon (i.e., associated with purchasing insurance). There are small, statistically significant differences between recipients and non-recipients in specific periods (gender in SRSD09 and LRLD11, dependency ratio and income in LRLD12) but none that systematically appear across all coupon distribution periods and no more than one would expect randomly. So premium discount coupon distribution indeed appears random, as designed.

**Table D1.** Test of balance between coupon recipients and non-recipients

| Season | Variable | No Coupon | Std. Err. | Coupon | Std. Err. | Difference | t_statistic |
|---|---|---|---|---|---|---|---|
| **SRSD09** | Head age | 47.10 | 3.18 | 48.6 | 2.78 | 1.52 | 0.36 |
| | Head gender | 0.58 | 0.06 | 0.61 | 0.05 | 0.03 | 0.34 |
| | Members | 5.02 | 0.19 | 5.16 | 0.16 | 0.14 | 0.57 |
| | Dependency Ratio | 0.56 | 0.03 | 0.63 | 0.01 | 0.07 | 1.86 ** |
| | Herd size (TLU) | 13.1 | 1.90 | 12.2 | 1.19 | -0.86 | -0.38 |
| | Income (Ksh/month) | 3,630 | 708 | 4,590 | 651 | 961 | 1.00 |
| | Asset Index | -0.27 | 0.06 | -0.08 | 0.09 | 0.19 | 1.73 * |
| | Consumption per AE | 1,590 | 108 | 1,680 | 129 | 80.8 | 0.48 |
| **SRSD10** | Head age | 45.9 | 3.12 | 48.2 | 2.31 | 2.25 | 0.58 |
| | Head gender | 0.62 | 0.06 | 0.53 | 0.05 | -0.08 | -1.03 |
| | Members | 5.28 | 0.21 | 5.42 | 0.19 | 0.14 | 0.51 |
| | Dependency Ratio | 0.64 | 0.02 | 0.61 | 0.02 | -0.03 | -1.00 |
| | Herd size (TLU) | 10.8 | 1.18 | 13.3 | 1.40 | 2.45 | 1.34 |
| | Income (Ksh/month) | 8,960 | 858 | 10,100 | 848 | 1,140 | 0.94 |
| | Asset Index | -0.45 | 0.03 | -0.39 | 0.05 | 0.06 | 1.02 |
| | Consumption per AE | 1,910 | 223 | 1,660 | 141 | -254 | -0.96 |
| **LRLD11** | Head age | 45.5 | 1.93 | 48.0 | 1.36 | 2.43 | 1.03 |
| | Head gender | 0.66 | 0.05 | 0.53 | 0.05 | -0.13 | -1.73 * |
| | Members | 5.71 | 0.20 | 5.69 | 0.17 | -0.02 | -0.06 |
| | Dependency Ratio | 0.53 | 0.03 | 0.58 | 0.02 | 0.04 | 1.30 |
| | Herd size (TLU) | 9.35 | 0.98 | 10.5 | 0.86 | 1.11 | 0.85 |
| | Income (Ksh/month) | 10,000 | 1,080 | 10,40 | 611 | 399 | 0.32 |
| | Asset Index | -0.22 | 0.07 | -0.12 | 0.05 | 0.10 | 1.13 |
| | Consumption per AE | 1,960 | 98.9 | 2,030 | 103 | 60.2 | 0.67 |
| **LRLD12** | Head age | 45.5 | 1.55 | 48.7 | 1.33 | 3.18 | 1.56 |
| | Head gender | 0.61 | 0.05 | 0.56 | 0.05 | -0.05 | -0.60 |
| | Members | 6.07 | 0.22 | 6.05 | 0.18 | -0.02 | -0.08 |
| | Dependency Ratio | 0.67 | 0.01 | 0.60 | 0.03 | -0.07 | -2.35 ** |
| | Herd size (TLU) | 8.73 | 0.91 | 9.29 | 0.75 | 0.56 | 0.47 |
| | Income (Ksh/month) | 10,800 | 1,030 | 14,400 | 1,470 | 3,610 | 2.02 * |
| | Asset Index | -0.02 | 0.05 | 0.12 | 0.07 | 0.14 | 1.54 |
| | Consumption per AE | 1,430 | 93.8 | 1,520 | 73.6 | 90.1 | 0.76 |

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

To be valid instruments, the discount coupon must also be correlated with demand for insurance. We test for correlation with both uptake (a dummy variable equal to one if the household purchased IBLI that season) and the continuous level of purchase, measured in TLUs of coverage. Our instrumental variable is a dummy variable equal to one if the household received a discount coupon. The size of the discount offered by the coupon is not used as an instrumental variable in this paper for the reasons described in Section 5.

**Table D2.** Predictive power of the discount coupons on purchases

| | Dummy (=1 if purchased) | Level (TLUs insured) |
|---|---|---|
| Coupon Dummy | 0.206*** | 0.541*** |
| | (0.028) | (0.076) |
| | | |
| Observations | 7,042 | 7,042 |
| F(2,1008) | 33.5 | 32.7 |
| $R^2$ | 0.225 | 0.128 |

Regression includes the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered and robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

*Appendix E: Pooled Instrumental Variables Estimates*

In the event that time invariant household characteristics do not play a role in our households' outcomes, the fixed effects model is inefficient and there may be statistically significant impacts of program participation that are not evident in the fixed effects estimates. Those estimates, found in Tables 6-8, are re-estimated in this appendix using a pooled model. We continue to use the instrumental variables described in the main body of the text (i.e., intent to treat for HSNP and discount coupons for IBLI). We also include a time invariant indicator is equal to one if the household participated in the IBLI educational game, which are random and have a positive impact on IBLI uptake (Jensen, Mude & Barrett 2014).

The pooled estimates are, for the most part, similar to the fixed effects estimates. The most significant changes are associated with HSNP participation reduction to herd size, and a much more ambiguous impact on household mobility and livestock mortality rates (Tables E1-E3).

**Table E1.** Impact of IBLI coverage and indemnity payments on household welfare (Pooled estimates)

| | HSNP | | IBLI | |
|---|---|---|---|---|
| | **Previous Participation** | **Current Participation** | **Previous Coverage** | **Current Coverage (TLU)** |
| Production strategies: | | | | |
| Herd Size | -1.619*** | -1.123 | -11.17*** | -0.196 |
| | (0.531) | (3.218) | (3.259) | (1.141) |
| | | [7.295] | | [7.545] |
| Veterinary Expenditures (KSH) | -52.31 | 277.7 | 319.3 | 109.4 |
| | (63.06) | (227.7) | (293.8) | (109.2) |
| | | [10.27] | | [8.774] |
| Veterinary Expenditures/TLU (KSH) | 29.86 | 55.64 | -108.2 | 5.226 |
| | (37.28) | (143.6) | (306.9) | (35.47) |
| | | [1.805] | | [1.853] |
| Ratio of Herd Held at Home | 0.000447 | -0.0598 | -0.0351 | -0.0667 |
| | (0.0158) | (0.0747) | (0.114) | (0.0531) |
| | | [10.51] | | [8.528] |
| Household is Partially or Fully Mobile [A] | 0.0108 | -0.0411 | -0.0963 | 0.0525 |
| | (0.0186) | (0.0807) | (0.131) | (0.0542) |
| | | [65.94] | | [58.68] |
| Production outcomes: | | | | |
| Milk income (KSH) | -25.74 | 1,090 | 934.9 | 1,905** |
| | (262.8) | (1,121) | (1,482) | (841.8) |
| | | [11.85] | | [10.88] |
| Milk income per TLU (KSH) | 95.12*** | -139.8 | 753.4*** | 197.5** |
| | (28.47) | (125.4) | (222.4) | (77.21) |
| | | [14.58] | | [12.14] |
| Livestock losses | -0.358* | 0.780 | -1.712* | 0.312 |
| | (0.190) | (0.983) | (0.882) | (0.424) |
| | | [8.537] | | [7.637] |
| Livestock Mortality Rate | 0.0571* | -0.0254*** | -0.0162 | 0.00216 |
| | (0.0317) | (0.00951) | (0.0481) | (0.0151) |
| | | [22.68] | | [22.12] |

Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. [A]A linear probability model is used to estimate the likelihood that a household is partially or fully mobile. Clustered and robust standard errors in parentheses. Model F-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1.

**Table E2.** The impact of shocks, HSNP participation, and IBLI coverage on livestock sales (TLUs)

| | HSNP Participation (IV) | IBLI Coverage (IV) |
|---|---|---|
| Shock | 0.168* | 0.199** |
| | (0.100) | (0.0972) |
| Participation/Coverage (P/C) | -0.247* | 0.0510 |
| | (0.136) | (0.0909) |
| P/C*Shock | 0.105 | -0.0775 |
| | (0.198) | (0.154) |
| | | |
| $H_0$: P/C + P/C *Shock=0 | -0.716 | -0.181 |
| t-statistic | | |
| | | |
| Observations | 6,567 | 6,573 |
| Model F-statistic | 6.303 | 6.689 |

The shock is an indicator that the division average livestock mortality rates in the current season are equal to or above 15%. Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table E3.** Impact of IBLI coverage and indemnity payments on household welfare

| | HSNP | | IBLI | |
|---|---|---|---|---|
| | **Previous Participation** | **Current Participation** | **Previous Coverage** | **Current Coverage (TLU)** |
| Consumption per AE | -85.87** | 620.8** | 170.8 | 0.377 |
| | (42.41) | (252.1) | (226.1) | (105.7) |
| | | [21.06] | | [20.20] |
| Asset Index | -6.506** | 56.11*** | 79.35*** | -18.34*** |
| | (3.089) | (16.01) | (20.66) | (5.841) |
| | | [17.13] | | [12.62] |
| Income per AE | -50.93 | 660.5* | 76.54 | 439.3** |
| | (48.13) | (364.7) | (333.4) | (179.8) |
| | | [21.95] | | [20.31] |
| School Absenteeism | -0.0957 | 0.222 | -0.0383 | 0.112 |
| | (0.160) | (0.849) | (0.832) | (0.305) |
| | | [11.98] | | [12.22] |
| School Enrollment | 0.0184 | 0.0616 | 0.0756 | 0.0518 |
| | (0.0201) | (0.0801) | (0.181) | (0.0365) |
| | | [16.32] | | [12.55] |
| WHZ | -0.0369 | 0.399 | -0.340 | 0.105 |
| | (0.160) | (0.508) | (0.528) | (0.369) |
| | | [5.405] | | [5.971] |
| MUAC | 0.0847 | 0.116 | -0.309 | 0.139 |
| | (0.112) | (0.353) | (0.383) | (0.178) |
| | | [5.957] | | [6.118] |

Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered robust standard errors in parentheses. Model F-statistic in brackets. *** p<0.01, ** p<0.05, * p<0.1.

*Appendix F: Asset Index*

The asset index is constructed using the factor loadings of a factor analysis on a set of household assets and construction materials similar to the process described in Sahn and Stifle (2000). The assets are divided into groups roughly by value as described in Table F1. The loadings generated from the first factor from the factor analysis and used to calculate each household's asset index are founding Table F2.

**Table F1.** Variables included in the factor analysis used to construct and asset index

| Variable | Description |
|---|---|
| Walls | =1 if walls are stone, brick, cement, corrugated iron or tin. =0 if walls are mud, wood, grass, sticks, leaves or constructed of various materials. |
| Floor | =1 if the floor is cement, tile or wood. =0 if floor is mud, sand or natural. |
| Toilet | =1 if facilities are flush or covered latrine (vented & unvented). =0 if facilities are uncovered pit latrine or none. |
| Light | =1 if main source of lighting is electricity, paraffin, gas, or solar. =0 if main source of lighting is flashlight, wood, candle or biomass residue. |
| Cook | =1 if main cooking appliance is jiko, stove, gas cooker, or electric cooker. =0 if main cooking is done on a traditional fire. |
| Fuel | =1 if the main cooking fuel is electricity, gas, paraffin, or charcoal. =0 if main fuel is wood. |
| Furniture | Total number of the following assets: metal trunks, mosquito nets, modern chairs, modern tables, wardrobes, mattresses and modern beds. |
| Water Source: | A set of mutually exclusive dummy variables indicating the household's main water source is: open and unprotected, a protected well, a borehole, a tap, rain, or from a water tanker. |
| Education | Maximum level of education in the household. |
| Cash | Cash holdings on-hand or held in a savings. |
| Land | Hectares of land owed. |
| Irrigation | Hectare of land irrigated. |
| Poultry | Number of poultry owned. |
| Donkeys | Number of donkeys owned. |
| Very small | Total number of the following assets: gourds, cups, scissors, and needle and thread sets. |
| Small tools | Total number of the following assets: anvils, panier, sickle, pickaxe, hoe, spade, machetes, spears, bows, club, chisels, hammers, files, fishing lines. |
| Small other | Total number of the following assets: musical instruments, traditional tools, bells, knifes, basins, sufirias, thermoses, buckets, wristwatches, jewelry |
| Medium tools | Total number of the following assets: Wheelbarrows, fishing nets, mobile phones, washing machines, spinning machines, weaving machines, sewing machines, bicycles, and plows. |
| Medium other | Total number of the following assets: water tank, jerry can, paraffin lamp, water drum, kerosene stove, charcoal stoves, ovens and radios. |
| Large | Total number of the following assets: animal carts, shops, stalls and boats. |
| Large with motor | Total number of the following assets: cars, motorbikes and tractors. |

**Table F2.** Factor loadings

| Variable | Description |
|---|---|
| Walls | 0.157 |
| Floor | 0.148 |
| Toilet | 0.111 |
| Light | 0.110 |
| Cook | 0.071 |
| Fuel | 0.053 |
| Furniture | 0.191 |
| Water Source: | |
| Open | 0.005 |
| Protected Well | 0.006 |
| Borehole | -0.006 |
| Tap | 0.035 |
| Rain | 0.038 |
| Water Tanker | 0.005 |
| Education | 0.072 |
| Cash | 0.045 |
| Land | 0.022 |
| Irrigation | 0.017 |
| Poultry | 0.039 |
| Donkeys | 0.003 |
| Very small | 0.029 |
| Small tools | 0.109 |
| Small other | 0.023 |
| Medium tools | 0.219 |
| Medium other | 0.146 |
| Large | 0.015 |
| Large with motor | 0.045 |

Division-period dummies included in factor analysis.

*Appendix G: Further Analysis of Households' Responses to Shocks*

Analysis of response to covariate shocks found that households increase livestock sales during covariate shock years but that neither HSNP participation nor IBLI coverage impact that response significantly (Table7). If households face a great deal of idiosyncratic risk, it may be that our covariate shock indicator misses many of the shocks that households face. To allow for individual shocks, we define a shock season as any season in which the household experiences greater than a 15% livestock mortality rate. By this definition, households face shocks in about 30% of our observations. Our analysis finds a pattern consistent with those from the covariate definitions of shock; that IBLI increases livestock sales in "non-shock" seasons and there is no evidence that IBLI reduces livestock sales during shock seasons.

**Table G1.** The relationship between individually defined shocks and IBLI coverage on sales of livestock

| | HSNP Participation | IBLI Coverage (TLUs) |
|---|---|---|
| Shock | 0.0957 | 0.173** |
| | (0.0731) | (0.0698) |
| Participation/ Coverage (P/C) | 0.173 | 0.129* |
| | (0.150) | (0.0710) |
| P/C*Shock | 0.169 | -0.124 |
| | (0.162) | (0.147) |
| H0: P/C + P/C *Shock=0 (z-statistic) | 1.573 | 0.0369 |
| Observations | 6,564 | 6,570 |
| Households | 897 | 897 |
| Model F-statistic | 4.786 | 5.052 |

The shock is an indicator that the household suffered livestock losses are a rate greater than 0.15 in that season. Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To test to the impact of current coverage and distress sales while controlling for past and coming shocks, we include both future and lagged shock dummies. Shocks are defined as any period during which covariate losses are greater than 0.15. The estimates continue to point towards little changes to sales associated with

HSNP participation and increased livestock sales by the insured during non-shock periods.

**Table G2.** Current livestock sales in response to past, current, and coming covariate shocks

| | **HSNP Participation (IV)** | **IBLI Coverage (IV)** |
|---|---|---|
| Past Shock (t-1) | -1.021 | -2.287 |
| | (4.478) | (5.583) |
| Shock (t) | -0.773 | -1.936 |
| | (4.291) | (5.244) |
| Coming Shock (t+1) | -0.222 | -0.827 |
| | (2.334) | (3.008) |
| IBLI Coverage (IC) | 0.791 | 0.492** |
| | (2.797) | (0.238) |
| IC*Past Shock | -0.0555 | -0.335 |
| | (1.595) | (0.273) |
| IC*Shock | -0.104 | -0.191 |
| | (0.879) | (0.164) |
| IC*Coming Shock | -0.0545 | -0.359 |
| | (1.856) | (0.234) |
| | | |
| Observations | 4,692 | 4,698 |
| Households | 836 | 836 |
| F-stat | 4.681 | 5.488 |

The shock is an indicator that the covariate loss rate is greater than 0.15 in that season. Both models include the following covariates: adult equivalence, age of head, age of head squared, maximum education in household, a dummy indicating the head of household is a widow, the current season's predicted livestock mortality rate, the current season's predicted livestock mortality rate squared, division-period dummies and the three HSNP targeting characteristics to the first, second, and third power. Clustered and robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.