DESIGNING INDEX BASED LIVESTOCK INSURANCE FOR MANAGING ASSET RISK IN NORTHERN KENYA

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Abstract

This paper describes a novel index-based livestock insurance (IBLI) product piloted among pastoralists in northern Kenya, where insurance markets are effectively absent and uninsured risk exposure is a main cause of poverty. We describe the methodology used to design the contract and its underlying index of predicted area-average livestock mortality, established statistically using longitudinal observations of household-level herd mortality fit to remotely sensed vegetation data. Household-level performance analysis based on simulated data finds that IBLI removes 25-40% of total livestock mortality risk. We describe the contract pricing and the potential risk exposure of the underwriter to establish IBLI's reinsurability on international markets.

Keywords: Drought risk management, index insurance, Kenya, livestock insurance, livestock mortality, NDVI, pastoralists, remote sensing, vegetation index, weather derivatives

1. Introduction

Formal insurance contracts are rarely available for the small scale agricultural and pastoral households who populate the often highly risky environments found in rural areas of low income countries. While a rich literature analyzes the wide array of informal social arrangements and diversification strategies that these households employ to manage risk, in nearly all cases these mechanisms are highly imperfect and in many cases carry very high implicit insurance premia. The net result is that risk contributes significantly to the level and persistence of rural poverty.

In response to this challenge, a small, but growing number of projects are trying to fill this insurance void by developing index insurance contracts that offer payoffs based on the realization of an aggregate performance indicator, or index, rather than on individual-specific outcomes.[1] Because it relies on an objectively and cost-effectively measured aggregate indicator – not manipulable by insured parties – index insurance is potentially viable in low income agriculture, where transactions costs, moral hazard and adverse selection typically cripple contracts based on individual-specific outcomes. A key challenge in developing effective index insurance revolves around identifying an index that minimizes the associated basis risk representing discrepancies between the contract's index-triggered indemnity payments and the insured's actual loss experience.

While index insurance principles thus seem to offer a way to reduce the costs of uninsured risk, most projects to date have insured stochastic income streams (*e.g.*, crop yield insurance), despite the fact that globally most insurance sold is actually asset insurance. This paper designs and implements a methodology for using satellite-based information to create asset insurance contracts for some of the poorest and most

[1] Alderman and Haque (2007), Barnett et al. (2008) and Skees (2008) offer helpful reviews.

vulnerable people on the planet, namely the pastoralist populations of the arid and semi-arid regions of East Africa.

Our focus on asset insurance is not accidental. Effective demand appears sluggish for the various agriculture index insurance contracts presently on offer to protect rural income streams. While there are a variety of reasons for this sluggishness,[2] one likely reason is that static income insurance offers the farmer a zero sum proposition: Does the farmer want to spend a fraction of a *given* income level on insurance, implying a reduction in spending on other goods and services?

Arguably, demand for insurance will be stronger and more sustainable when it offers the farmer a non-zero sum choice. Income insurance can become a non-zero sum proposition if it simultaneously underwrites an increase in expected income even as it reduces risk exposure. This positive sum game can happen if income insurance crowds in the adoption of new, higher-returning technologies, either by improving the supply of credit to purchase these technologies or by increasing farmers' willingness to bear the risk to borrow and otherwise adopt these technologies. By preserving productive assets for future periods, asset insurance similarly offers not just an effective buffer against current risk exposure but also higher expected incomes over time and thereby makes insurance a positive sum game. In environments that are characterized by asset-based poverty traps, like the East African rangelands, the positive sum nature of asset insurance can be especially strong.[3]

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[2] Reasons for sluggish demand include poorly designed insurance contracts that offer relatively little stability to household income streams; poor understanding of insurance amongst populations who typically have never had any form of insurance; credit constraints, and, lack of trust in the reliability of the insurance providers and their promise to appear with compensatory payments in an unknown time in the future (see for example, Giné et al. 2008, Cole et al. 2009).

[3] As further discussed in Section 2, an asset-based poverty trap occurs when a household becomes essentially economically non-viable if its holdings of productive capital fall below a critical threshold level. In this context, asset losses that push a household below that threshold can prove irreversible (at least in

While the logic of asset insurance for the pastoral regions of East Africa is compelling, the design of index insurance contracts for this environment faces a number of challenges if there is to be both supply of, and demand for these contracts. For the specific case of Marsabit District in Northern Kenya, this paper shows how satellite imagery can be used as the basis for contracts that can solve these challenges. Specifically, this paper shows how objectively measured satellite-based vegetation data available in near-real time can be combined with household-level herd data to create a livelihood-focused contract that minimizes basis risk and that seems to find a ready demand among pastoral households. We investigate the effectiveness of the contract by testing it out-of-sample using complementary household-level panel data from the same region as well as simulated household mortality data constructed from these panel data. Finally, the paper then analyzes several alternative pricing structures, and calculates the risk exposure that an insurance underwriter would face.

The remainder of the paper is organized as follows. Section 2 presents a brief overview of the risk and insurance problem in Northern Kenya, which typifies many remote, poor regions where household assets are routinely exposed to natural disaster risk. Section 3 proposes a livelihood-focused approach to index insurance design that uses micro data on household outcomes to establish an insurance index that minimizes uninsured basis risk. Section 4 then implements this design approach for the specific case of Northern Kenya, discusses estimation results for the predicted mortality index and analyzes the effectiveness of the proposed contract using an out-of-sample prediction methodology and household risk decomposition. Section 5 analyzes alternative strategies for pricing the proposed contract and performs risk exposure analysis for potential

expectation) and insurance against such losses should be especially valuable to the household (Carter and Barrett 2006).

insurers. Finally, Section 6 concludes with reflection on the implementation challenges that confront efforts to bring this kind of contract to market.

2. Risk and Irreversible Asset Loss in the Northern Kenya Pastoral Economy

The more than three million people who occupy northern Kenya's arid and semi arid lands (ASALs) depend overwhelmingly on livestock, which represent the vast majority of household wealth and account for more than two-thirds of average income. Livestock mortality is the most serious economic risk these pastoralist households face.

The importance of livestock mortality risk management for pastoralists is amplified by the apparent presence of poverty traps in east African pastoral systems, characterized by multiple herd size equilibria such that losses that push a household below a critical threshold – typically 8-16 tropical livestock units (TLUs)[4] – tend to tip a household into destitution (McPeak and Barrett 2001, Lybbert et al. 2004, Barrett et al. 2006). Put differently, livestock losses that push households below this threshold appear irreversible in expectation, or to at least have very severe, long-term consequences. Uninsured risk appears as the primary driver of such poverty traps amongst east African pastoralists (Santos and Barrett 2006).

Most livestock mortality is associated with severe drought. In the past 100 years, northern Kenya recorded 28 major droughts, 4 of which occurred in the last 10 years (Adow 2008). The climate is generally characterized by bimodal rainfall with short rains falling in October-December, followed by a short dry period from January-February. The long rain and long dry spells run March-May and June-September, respectively.

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

Pastoralists commonly pair rainy and dry seasons, for example observing that failure of the long rains results in large herd losses at the end of the following dry season.

Pastoralist households commonly manage livestock mortality risk ex ante, primarily through animal husbandry practices, in particular nomadic or transhumant migration in response to spatiotemporal variability in forage and water availability. When pastoralists suffer herd losses, there exist social insurance arrangements that provide informal inter-household transfers of a breeding cow. But these schemes cover mainly the idiosyncratic component of loss, and less than ten percent of household herd losses, on average, they do not include everyone and are generally perceived as in decline (Lybbert et al. 2004, Huysentruyt et al. 2009, Santos and Barrett forthcoming). Some households can draw on cash savings and/or informal credit from family or friends to purchase animals to restock a herd after losses. But the empirical evidence that vast majority of intertemporal variability in herd sizes in this region is biologically regulated, due to births and especially deaths (McPeak and Barrett 2001, Lybbert et al. 2004), implies that most livestock mortality risk remains uninsured.

Most uninsured herd mortality losses occur in droughts as covariate shocks affecting many households at once, sparking a humanitarian crisis (Chantarat et al. 2008, Mude et al. 2009). The resulting large-scale catastrophe induces emergency response by the government, donors and international agencies, commonly in the form of food aid. As the cost and frequency of emergency response in the region has grown, however, mounting dissatisfaction with food aid-based risk transfer has prompted exploration for more comprehensive and effective policies. One approach is to replace sporadic emergency transfers with systematic and reliable cash transfers. One such program is

currently underway in Northern Kenya.[5] Unfortunately, an implication of herd size tipping points in this region is that cash transfers to those who have collapsed into the low level poverty trap may prove ineffective in reducing long-run poverty by failing to prevent collapses into destitution. In this context, the development of risk transfer products to halt the collapse of households into a poverty trap thus has much to recommend it.[6] The most recent parliamentary campaign in Kenya included widespread, highly publicized promises by prominent politicians to develop livestock insurance for the northern Kenyan ASALs.

While there thus at least appears to be political demand for livestock insurance, will there actually be effective demand on the part of pastoral households? In an effort to gain some insight on this question, from May-August 2008 we undertook extensive community discussions in five locations in Marsabit District, surveyed and performed field experiments with 210 households in those same locations. Chantarat and Mude (2010), McPeak et al. (2010) and Lybbert et al. (2010) describe those studies, which confirmed (i) pastoralists' keen interest in an asset insurance product, (ii) their comprehension of the basic features of the index insurance product explained below, and (iii) some modest willingness to pay[7] for the product at a commercially viable premium – sufficient to support commercial implementation and market mediation. While experimental game-based and hypothetical willingness-to-pay measures based on survey

[5] Funded in part by the U.K. Department for International Development (DfID), and implemented by the Kenyan Ministry for the Development of Northern Kenya and other Arid Lands, the Hunger Safety Net Program targets indigent households with monthly transfers worth approximately $15.

[6] For a formal analysis, see Barrett, Carter and Ikegami (2008).

[7] Willingness-to-pay experiments in five representative locations (each with mean population of 900 households and mean herd sizes from 2-15 TLU in 2008) in Marsabit suggest that, on average, households are willing to insure 68.9% of their herd at 15% mark-up of the actuarially fair rates. Proportions of these representative households who are willing to pay at 20%, 30% and 40% mark-up rates reduce to 34%, 16% and 9% respectively with relatively lower price elasticity of demand among households with greater than 30 TLU herd sizes (Chantarat and Mude 2010).

responses are an imperfect guide to real-world behavior, these results do further motivate efforts to design and implement a real-world asset insurance contract for this region.

3. Demand-driven Design of Index Insurance

Index insurance contract design often focuses on obtaining and analyzing data on a signal, which we denote θ_{ls}, that is related to the assets or income streams in locality l in season or period s. Examples of such signals include local rainfall or other meteorological information, or average producer yields in the locality. From the perspective of ensuring a sustainable commercial supply of the insurance contract, it is vital that the signal be reliably measurable at low cost, and that its level not be influenced by the behavior of any insured individual nor by which subset of individuals purchase the insurance.

While these 'supply side' considerations are clearly important, so are the processing and mapping of this signal into an index that offers the best coverage for the insured party. These 'demand side' considerations are equally important if insurance is to provide a sustainable solution to the development problems created by uninsured risk and thereby generated sustainable commercial demand for such products.

In many cases, general agronomic information is used to process the untransformed signal that is used as the basis for a simple linear index. For example, if crop yields tend to fall as rainfall over a critical crop growth period falls below 120 millimeters, then the insurance contract simply states that payments begin and linearly increase for every millimeter shortfall in rainfall below 120.

While there is a clear logic to this approach, it suffers two disadvantages. First, it places the insurance index in what might be an exotic or unfamiliar unit of measure for the insurable population (e.g., millimeters of rain). Second, the simple linear mapping

between the signal and payouts may be a suboptimal use of the information contained in the signal in the sense that other mappings may more closely correlate with the household's asset or income that is being insured.

In an effort to deal with both of these problems, we take a regression-based approach to the design of the proposed asset insurance contract. In particular, denote a household-level measure of the livelihood outcome variable that is being insured as M_{ils}. In our case, M_{ils} is the livestock mortality (asset loss, measured in aggregate tropical livestock units or TLU) experienced by household *i* in locality *l* in season *s*. In other cases, this measure might be household output of a particular crop, household income, or even household consumption.[8] We can then write the realized TLU mortality rate of the pastoralist household *i* in location *l* over season *s* as:

(1) $$M_{ils} = \bar{M}_{il} + \beta_i(M_{ls} - \bar{M}_l) + \varepsilon_{ils}$$

where $\bar{M}_{il}$ reflects household *i*'s long-term average mortality rate, M_{ls} is the area average mortality rate at location *l* over season *s*, $\bar{M}_l$ is the long-term mean rate in location *l* and ε_{ils} reflects the idiosyncratic component of household *i*'s herd losses (e.g., from conflict, accident, etc.) experienced during season *s*, i.e., the household-specific basis risk. The parameter β_i determines how closely household *i*'s livestock mortality losses track the area average. If $\beta_i = 1$ then household *i*'s livestock losses closely track the area average, while $\beta_i = 0$ means *i*'s mortality losses are statistically independent of the area average. Over the whole location, the expected value of β_i is necessarily one.

[8] Note that household consumption reflects its various income streams as well as net flows of informal social insurance and perhaps other stochastic payments.

The area average livestock mortality rate can be orthogonally decomposed into systematic risk associated with observable signal θ_{ls} and the risk driven by other factors:

(2) $$M_{ls} = M\big(X(\theta_{ls})\big) + \varphi_{ls}$$

where $X(\theta_{ls})$ represents a transformation of the signal and $M(\cdot)$ represents the statistically predicted relationship between $X(\theta_{ls})$ and M_{ls}, and φ_{ls} is the component of area average mortality that is not explained by $X(\theta_{ls})$ – i.e., location-specific basis risk. We thus predict area average mortality from observations of θ_{ls}, specific to each location l and season s, as $\widehat{M}(\theta_{ls}) = M\big(X(\theta_{ls})\big)$, which serves as the underlying index for the insurance contract. Note that this index is expressed in units that are already known and meaningful to the insurable population (aggregate livestock mortality).

Equations (1) and (2) also imply that there are thus two sources of basis risk: (i) the household's idiosyncratic losses that are uncorrelated with area average losses according to (1) and (ii) area average mortality losses that are not explained by the underlying predicted mortality index, according to (2). Note also that the use of standard regression methodologies to estimate the relationship in (2) based on reliable household-level data will necessarily minimize basis risk for the insured party, on average.

An index insurance contract based on this predicted mortality index will thus function like a put option on predicted area average mortality rate. In the specific case of Northern Kenya where there are two distinct seasons per year, we can define a seasonal index insurance contract that pays an indemnity beyond the contractually-specified strike mortality level, M^*, conditional on the realization of the index $\widehat{M}(\theta_{ls})$ according to[9]:

[9] Note that we can also generalize this linear payoff function to create a non-linear payoff scheme that would offer better insurance value (for a given premium) assuming a conventional expected utility approach to risk. To keep things simple, we concentrate on the simple linear payoff version here.

(3) $\Pi_{ls}\left(\widehat{M}(\theta_{ls})|\, M^*, TLU, P_{TLU}\right) = max\left(\widehat{M}(\theta_{ls}) - M^*, 0\right) \times TLU \times P_{TLU}$

where TLU is the total TLU of livestock insured and P_{TLU} is the pre-agreed value of 1 TLU, so that their product reflects the total insured livestock value. The expected insurance payout thus represents the actuarially fair premium for this contract and so we can write the actuarially fair premium rate quoted as percentage of total value of livestock insured as $p_l\left(\widehat{M}(\theta_{ls})|\, M^*\right) = E\left(max\left(\widehat{M}(\theta_{ls}) - M^*, 0\right)\right)$, where $E(\cdot)$ is taken over the distribution of the observable signal θ_{ls}.

Using the seasonal payout function in (3), we can further consider a one-year contract bundling two consecutive seasonal contracts with total insurance payout – to be paid twice at the end of each coverage season *s* or all at once at the end of year *t*. In this setting, the seasonal payout appears more suitable – in contrast to a yearly payout – because pastoralists' financial illiquidity typically means that catastrophic herd losses threaten human nutrition and health in the absence of prompt response (Mude et al. 2009). The rapid response capacity of seasonal insurance contracts of this approach to drought risk management compares favorably with traditional reliance on food aid shipments, which typically involve lags of five months or more after the onset of a disaster (Chantarat et al. 2007).

4. Designing an Index-based Livestock Insurance for Northern Kenya

4.1 Data description

As our basic signal that forms the backbone for the Northern Kenya asset insurance, we employ an objectively, real-time measured Normalized Difference Vegetation Index (NDVI). NDVI – sometimes referred to as "greenness maps," – is a satellite-derived indicator of the amount and vigor of vegetation, based on the observed level of

photosynthetic activity (Tucker 2005). The NDVI data that we use are computed reliably at high spatial resolution (8 km^2 grids) and consistent quality from Advanced Very High Resolution Radiometer (AVHRR) on board of the United States National Oceanic and Atmospheric Administration (NOAA) satellite, and have been available in real time every 10 days (called a "dekad") with the longest temporal profile since late 1981.[10]

Because pastoralists routinely graze animals beyond their residential areas, we define the grazing range for each aggregate location – within which NDVI observations are averaged for each period – by identifying the rectangle that encompasses the residential locations and all common animal water points used by herders in that community, plus 0.1 decimal degrees (about 11 kilometers) in each direction.[11] In bad years not observed in the survey data, pastoralists may travel further still, but their need to do so should be reflected in pasture conditions within their normal grazing range. NDVI data are commonly used to compare the current state of vegetation against the long-term average condition in order to detect anomalies and to anticipate drought (Peters et al. 2002, Bayarjargal et al. 2006) and have now been used by many studies that apply remote sensing data to drought management (Kogan 1990, 1995, Benedetti and Rossini 1993, Hayes and Decker 1996, Rasmussen 1997).

[10] The NDVI images collected by NOAA-AVHRR are then processed by the Global Inventory Monitoring and Modeling Studies (GIMMS) group at the National Aeronautical and Space Administration (http://gimms.gsfc.nasa.gov/) to produce NDVI data series. The scanning radiometer (comprised of five channels) is used primarily for weather forecasting. However, there are an increasing number of other applications, including drought monitoring. NDVI is calculated from two channels of the AVHRR sensor, the near-infrared (NIR) and visible (VIS) wavelengths, using the following algorithm: NDVI = (NIR - VIS)/(NIR + VIS). NDVI is a nonlinear function that varies between -1 and +1 (undefined when NIR and VIS are zero). Values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation. Further details about this NDVI source are available at http://earlywarning.usgs.gov/adds/readme.php?symbol=nd.

[11] Georeferenced water point data and locations of representative households are available for the studied locations.

We rely on NDVI data for two reasons. The first is conceptual. Catastrophic herd loss is a complex, unknown function of rainfall – which affects water and forage availability, as well as disease and predator pressure – and rangeland stocking rates – which affect competition for forage and water as well as disease transmission. Rangeland conditions manifest in vegetative cover reflect the joint state of these key drivers of herd dynamics. When forage is plentiful, disease and predator pressures are typically low and water and nutrients are adequate to prevent significant premature herd mortality. By contrast, when forage is scarce, whether due to overstocking, poor rainfall, excessive competition from wildlife, or other pressures, die-offs become frequent. Thus a vegetation index makes sense conceptually.

The second reason is practical. Kenya does not have longstanding seasonal or annual livestock census surveys of the sort used for computing area average mortality, the index used in the developing world's other IBLI contract, in Mongolia (Mahul and Skees 2005). The household-level herd mortality data we use in contract design are collected for the Government of Kenya, which might have a material interest in IBLI contract payouts, thereby rendering those data unsuitable as the basis for the index itself. Consistent weather data series at sufficiently high spatial resolution are likewise not available. The Kenya Meteorological Department station rainfall data for northern Kenya exhibit considerable discontinuities and inconsistent and unverifiable observations. Meanwhile, rainfall estimates based on satellite-based remote sensing remain controversial within climate science.[12]

[12] Remotely sensed data capture precipitation emergent from cloud cover, not rain that lands on Earth. As a result, the validity of those measures remains subject to much dispute within the climate science community (de Goncalves et al. 2006, Kamarianakis et al. 2007).

In order to implement the demand-driven contract design methodology discussed in the prior section, we analyze a combination of household-level livestock mortality data collected monthly since 1996 in various representative locations by the Government of Kenya's Arid Land Resource Management Project (ALRMP, http://www.aridland.go.ke/) and dekadal (every 10 days) NDVI data. We also employ household-level panel data collected quarterly by the USAID Global Livestock Collaborative Research Support Program Pastoral Risk Management (PARIMA) project (Barrett et al. 2008) to analyze and simulate the IBLI contract's performance out of sample. The use of NDVI data is uncommon in index insurance design, especially in the developing world. The use of household-level panel data in index insurance contract design and evaluation is, to the best of our knowledge, unique to this contract.

We focus specifically on what was until recently Marsabit District, where the ALRMP data are most complete and reliable, offering monthly repeated household survey data from January 2000 to January 2008 in 7 representative locations.[13] It is thus possible to construct location-averaged seasonal herd mortality rate for each location for 8 consecutive long rain-long dry seasons (the period from March-September) and 8 short rain-short dry seasons (from October-February), providing a minimally adequate sample size of 112 location-and-season specific observations.

As sample households vary untraceably by survey round, we rely on monthly herd mortality average per household for each location, $\bar{M}_{lm}$, to construct seasonal location average mortality rate, M_{ls} , according to

[13] In 2008 the District was broken into three new Districts: Chalbi, Laisaimis and Marsabit. According to 1999 census and ALRMP 2000-2008 data, these studied locations situate on areas range from 2,535-5,260 km^2 for the 3 locations in the Chalbi area in the north to 1,160-1,935 km^2 for the other 4 in the south (see Figure 1). Population sizes range from 556-1,100 households with mean herd sizes from 9-25 TLU.

$$(4) \qquad M_{ls} = \frac{\sum_{m \in s} \bar{M}_{lm}}{\max_{m \in s} \bar{H}_{lm}}$$

where $\bar{H}_{lm}$ is monthly beginning herd size averaged per household for each location, and season s represents either the long rains-long dry (LRLD, March-September) or the short rains-short dry (SRSD, October-February) paired season. Because the livestock mortality data do not distinguish between mature and immature animals, mortality rates are inflated for any months in which newborn calves died in large number; hence our use of the maximum $\bar{H}_{lm}$ in computing the seasonal average. Note that area average mortality rates are, by definition, measures of covariate livestock asset shocks within those locations. By insuring area average (predicted) mortality rates, IBLI addresses the covariate risk problem but leaves household-specific, idiosyncratic basis risk uninsured.

There is considerable heterogeneity within the Marsabit region, as reflected in Table 1. We therefore performed statistical cluster analysis to identify locations with similar characteristics, generating two distinct clusters of three to four locations each (Figure 1). The Chalbi cluster is characterized by more arid climate, camel- and smallstock (i.e., goats and sheep) based pastoralism by the Gabra and Borana ethnic groups. The Laisamis cluster enjoys slightly higher (and more variable) rainfall and forage, hence its greater reliance on cattle and smallstock by the Samburu and Rendille.

Table 1 also reports seasonal mortality rates by location.[14] Locations in Chalbi (Laisamis) cluster experienced relatively higher and more variable mortality rate during the SRSD (LRLD) season. The differences are statistically significant between seasons within each cluster and between clusters within each season. Mortality rates are highly

[14] For the 7% of missing observations we interpolated monthly average livestock mortality rates using the average values of other available locations within the same cluster.

correlated within the same cluster (correlation coefficients of 0.80-0.95), while correlations between clusters are less. As Figure 2A shows, the 2000 and 2005-06 years exhibited the highest mortality losses during this period. Mortality rates are low – uniformly less than 20%, typically less than 10% – outside of these severe drought periods. Overall the frequency of area average mortality rates exceeding 10% is approximately 33% (a 1-in-3 year event) for both Chalbi and Laisamis. However, differences between the two clusters' mortality loss distributions can be shown in Figure 2B, where probability of extreme (in-between) risk is larger (smaller) for Chalbi comparing to Laisamis cluster.

During the same period as the ALRMP data collection, the PARIMA project undertook an intensive household panel survey in northern Kenya and southern Ethiopia, interviewing households quarterly. Four PARIMA locations are in our targeted Marsabit district with two belonging in each cluster. Two of these locations – Logologo and North Horr – exist in both household data sets. Although the shorter duration (4 seasons in 2000-2002 only) of the PARIMA survey provides insufficient observations to estimate the IBLI contract model (described below), we can use the higher quality PARIMA panel data to verify the aggregate reliability of the ALRMP data and to evaluate the performance of the IBLI contract out-of-sample.

Although there are very slight differences in herd data measurement, we can use the PARIMA data as a check on the ALRMP data by regressing season-and-location-specific PARIMA herd mortality rates data (n=8) on ALRMP rates in a simple univariate linear model. We cannot reject the joint null hypothesis that the intercept equals zero and the slope equals one in that relation ($F(2,6) = 0.01$ and p-value = 0.99). Thus the ALRMP data seem to capture area-average seasonal mortality reasonably well and the PARIMA

data permit unbiased out-of-sample evaluation of IBLI contracts based on the ALRMP herd mortality data and NDVI measures.

4.2 Optimizing Contract Design to Minimize Basis Risk

In order to specify the contract, we now describe how $X(\cdot)$ and $M(\cdot)$ are specified to allow for reasonable out-of-sample forecast performance.[15] Because the empirical relationship between rangeland conditions and livestock mortality appears to vary conditional on the climate regime, as reflected in the cumulative state of the rangeland, a regime switching model is used to estimate the relationship $M(\cdot)$ for each cluster as

$$(5) \quad M_{ls} = \begin{cases} M_1\big(X(ndvi_{ls})\big) + \varepsilon_{1ls} & if\ Czndvi_pos_{ls} \geq \gamma \quad (good\ climate\ regime) \\ M_2\big(X(ndvi_{ls})\big) + \varepsilon_{2ls} & if\ Czndvi_pos_{ls} < \gamma \quad (bad\ climate\ regime) \end{cases}$$

where a regime switching variable, $Czndvi_pos_{ls}$ (defined precisely below) determines the climate regime into which each season belongs with the γ critical threshold parameter determined endogenously. This regime switching specification allows us to estimate two different relationships conditional on the state of rangeland vegetation. We now describe how we construct our vegetation variables, $X(ndvi_{ls})$.

We first control for differences in geography (e.g., elevation, hydrology, soil types) across our locations by standardizing the raw NDVI data with pixel- and time-specific moments into the standardized NDVI:

$$(6) \qquad zndvi_{pdt} = \frac{ndvi_{pdt} - E_{pd}\big(ndvi_{pdt}\big)}{S_{pd}\big(ndvi_{pdt}\big)}$$

[15] This prevents us from overfitting the data.

where $ndvi_{pdt}$ is the NDVI for pixel p for dekad d of year t, $E_{pd}(ndvi_{pdt})$ is the long-term mean of NDVI for dekad d of pixel p taken over 1982-2008 and $S_{pd}(ndvi_{pdt})$ is the long-term standard deviation of NDVI for dekad d of pixel p taken over 1982-2008. Positive (negative) $zndvi_{pdt}$ represents relatively better (worse) vegetation conditions relative to the long-term mean. For each location l, the representative $zndvi_{ldt}$ can then be derived by averaging all $zndvi_{pdt}$ of all the pixels that fall within the location's boundaries. Figure 3 depicts the NDVI and zndvi series for the Marsabit locations.

Unlike crop yields that respond only to current season climate variables, livestock mortality can be the result of several seasons' cumulative effects (Chantarat et al. 2008). The lagged effects of exogenous variables raise a difficult tradeoff, however. Price stability is appealing from a product marketing perspective. Yet seasonal variation in premium rates in response to changing initial conditions enables insurers to guard against intertemporal adverse selection problems that may arise if prospective contract purchasers understand the state-dependence of livestock mortality probabilities.

So as to minimize the tradeoff between price instability and intertemporal adverse selection, we model the predictive relationship using the shortest lag structure possible – including only results from the preceding season – that still allows us to control for path-dependence. Therefore, the regime switching variable and some of the multiple regressors for estimating (5) are constructed as functions of cumulative zndvi beginning during the season before the contract period begins. These variables are constructed as follows and depicted in Figure 4A, which matches the seasonal IBLI contract structure with these cumulative vegetation index variables.

Because we want the regime switching variable, $Czndvi_pos_{ls}$, to represent the cumulative vegetation state and to be unobserved by all parties when the contract is struck, we use the year-long cumulative zndvi that starts from the beginning of the preceding rainy season until the end of the coverage season. Thus, with the cumulative period $T_{pos,s}$ covering the first dekad of October (March), until the end of the contract period season, i.e., the last dekad of September (February) for s = LRLD (SRSD):

(7) $$Czndvi_pos_{ls} = \sum_{d \in T_{pos,s}} zndvi_{lds}$$

When $Czndvi_pos_{ls} < 0$, this implies a worse than normal year, so we loosely term it a "bad climate regime," although this could be due to stocking rate or other drivers, not just climate conditions. We observe that all past major droughts fell into this regime.[16] The three constructed cumulative vegetation regressors are now described in turn.

$Czndvi_pre_{ls}$ reflects the state of the rangeland at the commencement of the contract period. This variable captures cumulative zndvi from the start of the preceding rainy season until the start of the contract season. Thus with the cumulative period $T_{pre,s}$ covering the first dekad of October (March), until the beginning of the contract period season, i.e., the first dekad of March (October) for s = LRLD (SRSD):

(8) $$Czndvi_pre_{ls} = \sum_{d \in T_{pre,s}} zndvi_{lds}$$

Since more degraded initial conditions drive up the likelihood of livestock mortality, this variable should negatively affect predicted area average seasonal mortality. Because the insurer must set the price before prospective IBLI purchasers make their insurance decisions, the latter may have superior information, leading to some level of

[16] Estimation of (5) also verified the intuition that $\gamma = 0$ by solving for the threshold value γ that maximizes goodness of fit.

intertemporal adverse selection. Because most of the observations are known ex ante to both parties, however, that effect should be minimal.

Analogous to the concept of cooling or heating degree days widely used in weather derivatives contracts, $Czndvi_n_{ls}$ captures the accumulation of negative zndvi, while $Czndvi_p_{ls}$ captures the accumulation of positive zndvi over the coverage season. And so for the contract season T_s covering March-September (October- February) for the LRLD (SRSD) season,

(9) $$Czndvi_n_{ls} = \sum_{d \in T_s} |min(zndvi_{lds}, 0)|$$

(10) $$Czndvi_p_{ls} = \sum_{d \in T_s} max(zndvi_{lds}, 0)$$

These two variables thus capture the cumulative intensity of adverse (favorable) dekads within the contract period. Catastrophic drought seasons routinely exhibit a continuous downward trend in cumulative zndvi leading to a large value for $Czndvi_n_{ls}$, which should have a significantly positive impact on mortality. Similarly, $Czndvi_p_{ls}$ permits us to control for post-drought recovery, when stocking rates have fallen and thus rangelands recover quickly, a phenomenon typically reflected in upward trending cumulative zndvi. This was the pattern observed, for example, in the SRSD seasons of 2001 and 2006 following catastrophic droughts the preceding LRLD seasons. Since these two variables capture only observations after the commencement of the contract, there is no information asymmetry with respect to these variables.

Overall, these cumulative vegetation variables[17] thus capture not only the adverse climate impact resulted from the preceding and current rain season, but also the intensity

[17] We also estimated a simple linear trend in the raw NDVI, zndvi data and all the constructed vegetative indices using least-squares linear regression. No significant trend was evident in the NDVI series for 6 of the 7 locations (Karare is the exception, with a significantly negative trend). We therefore did not attempt

of adverse climate. They also effectively capture the myriad, complex interactions between climate and stocking rates that are ultimately reflected in rangeland conditions and livestock mortality rates. We estimate simple linear regressions within each of the two regimes using the most parsimonious specification that fits the data well. With only eight years of data available for each location, limited degrees of freedom preclude estimating location-specific predictive models.[18] We therefore pool locations within the same cluster – treating each location's data as an iid draw from the same cluster-specific distribution – to estimate a cluster-specific predictive relationship, which we term a "response function". We also pool data for both LRLD and SRSD seasons but include a seasonal dummy to control for the potential differences across the two seasons. Figure 4B presents the temporal structure of a seasonal or annual IBLI contract designed using these predicted area average mortality indices constructed from these livelihood-linked response functions.

4.3 Estimation Results and Out of Sample Forecasting Performance

The estimation results for equation (5) are reported in Table 2 in comparison with other linear regression specifications.[19] The regime-switching models explain area average mortality reasonably well especially in the bad-climate regime, with an overall adjusted R^2 of 52% and 61% for Chalbi and Laisamis clusters, respectively. Livestock mortality patterns in the good climate regime are very difficult to explain, with no statistically significant relationship between any vegetation regressor and livestock mortality in the

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to detrend the data in this study. Descriptive statistics of the constructed NDVI variables and mortality data are reported in Appendix Table A1.

[18] Insurance companies would be unlikely to implement contracts at such high spatial resolution anyway, so this is not a serious problem.

[19] Table 2 shows that the regime switching specification that allows for different response functions for bad and good climate regimes significantly outperforms the model that estimates a uniform response function based on pooled data.

regime switching estimations and with very low adjusted R^2 in the regime-specific linear regression estimation. This makes intuitive sense as variation in good range conditions should not have a systematic effect on livestock survival.[20]

In the bad-climate regime, however, we see precisely the patterns anticipated. The initial state of the system, as reflected in $Czndvi_pre_{ls}$, has a very strong, statistically significant negative effect on mortality rates; the "less bad" the recent rangeland conditions when the insurance contract period falls into the bad climate regime, the lower is observed herd mortality. Similarly, the greater the intensity of positive (negative) spells during the season, as reflected in $Czndvi_p_{ls}$ ($Czndvi_n_{ls}$), the lower (higher) herd mortality rates, although those coefficient estimates are statistically significant only in Laisamis cluster, where pastoralists are less migratory and thus livestock are more sensitive to spells of unfavorable or favorable conditions during the season.

The regression coefficient estimates are themselves of limited interest. The real question is whether the predictions of livestock mortality prove sufficiently accurate to serve as a reasonable index on which to write livestock insurance contracts for the region. In addition to the basis risk portion of livestock mortality in the location that the model inherently cannot explain, there is also the possibility of error if the model specification and parameters chosen based on the ALRMP sample imperfectly reflect the true state of the system in explaining area average livestock mortality. One, therefore, wants to test how significant those errors are when new data are taken to the predictive model that generates the index on which IBLI is based.

[20] In the Chalbi model, the regime switching variable seemed to provide better explanatory power of livestock mortality in a bad-climate regime than the set of NDVI regressors. We therefore estimate the regime switching model for Chalbi using this switching variable as a regressor in the good climate regime.

The limited size of the ALRMP sample, however, precludes setting aside some of those data for out of sample performance evaluation. But we can test out of sample forecast accuracy using the PARIMA survey data, which cover four seasons (2000-2002) in four locations (Kargi and North Horr in Chalbi cluster, and Logologo and Dirib Gumbo in Laisamis cluster) in the same region, but were not used to estimate the predictive model.

Predicted seasonal area average mortality rates for studied locations, $\widehat{M}(ndvi_{ls})$, were first constructed based on the cluster-specific response functions established using the ALRMP livestock mortality data and location-specific NDVI data from 1982-2008. Figure 5 presents empirical distributions of the indices by cluster. Out-of-sample forecast errors reflecting the difference between actual PARIMA area average mortality rate and the predicted index (φ_{ls} in (2), which represents both unexplained mortality losses and the prediction error from the regression model) were then constructed and shown to nicely fall within 10% in absolute magnitude at 88% probabilities (n=8) for each cluster, with one single observation off by more than 25% in Dirib Gumbo and North Horr in the 2000 SRSD season (Appendix Table A2).

Next, we tested the performance of the IBLI contract in correctly triggering insurance payouts at different strike levels. The errors of greatest concern are when the insured are paid when they should not have been (type 1 errors) or not paid when they should have been (type 2 errors). Table 3 reports those results. The minimum frequency of correct decisions out of sample is 75%, with 94% overall accuracy (averaging Chalbi and Laisamis clusters) at a strike level of 15% mortality on the IBLI contract.

As another diagnostic over a longer period, we compare severe drought events reported by the communities with the predicted area average mortality indices

constructed from 1982-2008. We find the predicted mortality index quite accurately captures the regional drought events of 1984, 1991-92, 1994, 1996, 2000 and 2005-06, predicting average herd mortality rates of 20-40% during those seasons and never generating predictions beyond 10% in seasons when communities indicate no severe drought occurred.[21] This is a more statistically casual approach to forecast evaluation, but encompasses a longer time period and we have found it effective for communicating to local stakeholders the potential to use statistical models to accurately capture area average livestock mortality experience for the purposes of writing IBLI contracts.

4.4 Performance of Index-based Livestock Insurance for Individual Households

Following equations (1) and (2), the performance of IBLI turns on how well the predicted mortality index explains the insurable risk at a household level in the presence of both individual- and location-specific basis risks. We assess this using simulated seasonal livestock mortality data for 2000 households – 500 households for four locations: North Horr and Kargi (Dirib Gombo and Logologo) in Chalbi (Laisamis) cluster. The details on the household simulations, based on the PARIMA panel data and 53 seasons of NDVI data (1982-2008), are presented in Chantarat et al. (2010).[22]

Table 4 reports these household-level results. Overall, there is a 82% probability that the predicted mortality index also strikes the 10% contract when household's

[21] Figures depicting the time series of predicted mortality indices, by location, are available from the authors by request.

[22] Chantarat et al. (2010) uses the PARIMA household-level panel herd mortality data and the predicted mortality index constructed from 1982-2008 dekadal NDVI data to estimate the model: $M_{ils} = \mu_{il} + \beta_{il}\left(\widehat{M}(ndvi_{ls}) - E\left(\widehat{M}(ndvi_{ls})\right)\right) + \xi_{ils}$, which allowed us to decompose household-specific livestock mortality loss into the covariate component explainable by the insurable index and the component that is uncorrelated with the index. A vector of household-specific basis risk determinants, $\{\mu_{il}, \beta_{il}, \xi_{ils}\}$ – capturing both location- and household-specific basis risk – was then estimated using a random coefficients estimator. Household-specific livestock mortality rates were simulated based on the historical distribution of NDVI and the estimated location-specific best-fit distributions of these estimated parameters.

mortality loss exceeds 10%. These probabilities decrease at higher levels of household livestock losses, to 40% at a strike level of 20%, and to 54% at a strike level of 30% mortality loss. The 10% contract thus seems to provide coverage with the lowest type II errors in triggering decision.

Given that the mortality index correctly triggers indemnity payout, shares of households' insurable losses – beyond a particular strike – explained by the index are then estimated using a simple risk decomposition method.[23] The results show that as the contract strike level rises, the share of households' actual mortality losses covered by the triggered index increases from 25% for the 10% strike contract to 73% for the 30% strike one, demonstrating that this index works best for covering catastrophic losses. Combined with the probabilities of correct trigger decision, the average share of insurable losses explained by the index increases with household's loss experience, from an average share of 21% to 39% for household losses beyond 10% and 30%, respectively. The IBLI contract appears most effective in protecting households from more extreme covariate livestock mortality losses, which are effectively uninsured under existing informal risk management mechanisms (Lybbert et al. 2004, Huysentruyt et al. 2009).

5. Pricing and Risk Exposure Analysis

5.1 Conditional and Unconditional Contract Pricing Options

The actuarially fair premium of IBLI contracts can be calculated by taking an expectation of the indemnity payment function (3) per insured TLU over the historical (burn rate approach), estimated or simulated distribution of the underlying NDVI data. The contract

[23] If we regress the household individual mortality loss beyond each strike k on the indemnity payout based on the predicted mortality index: $M_{ils} - M_k^* = b_k\left(\widehat{M}(ndvi_{ls}) - M_k^*\right) + \nu_{ils}$, we can derive the share of insurable losses explained by the index at each strike k as $b_k \cdot \sigma\left(\widehat{M}(ndvi_{ls})\right)/\sigma(M_{ils})$.

can be designed as a seasonal contract that makes indemnity payouts in either season (SRSD or LRLD) or an annual contract that combines two consecutive seasonal contracts with two possible payouts per year, as depicted in Figure 4.

The top panel of Table 5 reports means (actuarially fair premium rates[24]) and standard deviations of the insurance payout rates (quoted as a percentage of insured herd value) for an annual contract calculated using the burn rate approach based on 27-year historical NDVI data (1982-2008). Because episodes of high predicted die-offs are more frequent in Chalbi than in Laisamis (Figure 5), fair premium rates are likewise higher there. Overall, the annual fair premium rates are 8.7% (5.5%), 5.2% (3.3%) and 2.7% (1.4%) of the insured livestock value for Chalbi (Laisamis) locations for coverage beyond 10%, 15% and 20% mortality rates, respectively. Premium loadings (proportional to the fair premia or S.D. of the indemnity payment rates) will further be applied to cover an insurer's other risks and transaction costs. Depending on the pastoralist's location and chosen strike rate, a herder needs to sell one goat or sheep to pay for annual insurance on 1-10 camels or cattle, an expense they appear willing to incur (Chantarat et al. 2010, Chantarat and Mude 2010).

The above contract can be fine-tuned to make pricing season-specific. Because expected mortality depends on the state of the system, the probability of catastrophic herd loss increases with rangeland vegetation conditions observable prior to the contract purchase. In order to guard against intertemporal adverse selection, insurers might adjust insurance premia. The bottom panel of Table 5 illustrates the simplest way to do so by pricing the contract conditional on the observed cumulative zndvi from the beginning of

[24] The US dollar equivalent premia per TLU insured can then be computed using an average value per TLU of KSh12,000 (approximately US$150 at November 2008 exchange rates at 79.2KSh/US$), per data we collected in these locations in summer 2008. Overall, the premia per TLU range from $13.1 (8.5) for 10% contract to $7.8 (5.0) for 15% contract and to $4.1 (2.1) for 20% contract.

the last rainy season until the beginning of the sale period, $Czndvi_beg_{ls}$, covering the preceding October-December (March – July) for LRLD (SRSD) contracts, assuming a two month sales period in January-February (August-September).

Using the pre-conditional threshold $Czndvi_{beg_{ls}} = 0$ analogous to that found in our earlier estimation, the two conditional annual premia are shown to vary markedly. For contracts with a 15% strike (currently piloted in northern Kenya), when the ex ante rangeland state is favorable, premia are only 3.1% (0.5%) for Chalbi (Laisamis) locations. But when the state of nature is bad, those rates jump to 6.6% (5.2%). Given marketing and political considerations, it is unclear whether insurers will be willing to vary IBLI premia in response to changing ex ante range conditions, leaving open a real possibility of intertemporal adverse selection with respect to the actual product offered.

5.2 Risk Exposure of the Underwriter

As we discussed in the introduction to this paper, covariate risk exposure is a major reason why private insurance fails to emerge in areas like northern Kenya, where climatic shocks like droughts lead to widespread catastrophic losses. IBLI to provide covariate asset risk insurance can effectively address the uninsured risk problem faced by pastoralists only if underwriters can manage the covariate risk effectively, perhaps through reinsurance markets or securitization of risk exposure (e.g., catastrophe bonds). We now explore the potential underwriter risk exposure of the proposed IBLI contract.

We estimate underwriter risk exposure under the following assumptions. First, we assume equal insurance participation covering 500 TLU in each of ten locations[25] in Marsabit for a total liability of $75,000/location. A standard insurance loss ratio for this

[25] These ten locations are the seven used for index construction plus three others in which we have gathered household and NDVI data; Balesa and Kargi in Chalbi cluster and Dirib Gumbo in Laisamis cluster .

portfolio in any insured year can be calculated by dividing total indemnity payments by pure premium collected for the total liability in the portfolio. The loss ratio thus provides a good estimate of the covariate risk that remains after pooling risk across locations.

Figure 6 illustrates cumulative distributions of the loss ratios[26] for this particular portfolio at 15% strike by pricing method and years of portfolio risk pooling. Over the full period, the loss ratio exceeds one roughly one year in three. State-conditional pricing and a longer-term commitment are shown to each reduce extreme outcomes sharply despite the fact that the reduced loss exposure risk necessarily comes at the cost of lower probability of large profits from the contract. With premium loadings, underwriter risk exposure would be reduced further relative to these estimates based on pure premia.

We now consider a simple reinsurance strategy where the loss beyond 100% of the pure premium is transferred to a reinsurer. For contracts with unconditional (conditional) premia, actuarially fair stoploss reinsurance rates quoted as percentage of IBLI premium would range from 49-68% (32-49%) for 10-30% strike contracts and with the rates of 53% (35%) for the piloted 15% strike contract (Appendix Table A3). These estimated pure reinsurance rates only take into consideration the local drought risk profile, however, and should fall as international reinsurers are better able to diversify these risks as part of their global insurance portfolio and in international financial markets. Indeed, this diversification opportunity through international risk transfer is one of the key benefits of developing IBLI products.

6. Conclusions and implementation challenges

[26] Temporal profiles of yearly loss ratios for various strike levels and under conditional and unconditional pricing can be provided by the authors upon request.

This paper has laid out why index based livestock insurance (IBLI) is attractive as a means to fill an important void in the risk management instruments available to pastoralists in the arid and semi-arid lands of east Africa. It then explained and evaluated the design of an IBLI product that was recently commercially piloted in northern Kenya to insure against covariate livestock mortality risk. The resulting index performs very well out of sample, both when tested against other household-level herd mortality data from the same region and period and when compared qualitatively with community level drought experiences over the past 27 years. Household-level performance analysis also indicates that IBLI is most effective in protecting households from otherwise-uninsured catastrophic covariate risks. Finally, we established that IBLI should be readily reinsurable on international markets.

The development of the IBLI contract opens up the opportunity to deliver commercially sustainable insurance in a place where uninsured risk remains a main driver of persistent poverty. The basic design should be replicable in other locations where covariate risk exposure is significant and existing insurance products do not adequately meet households' insurance needs. Extended time series of remotely sensed data are available worldwide at high quality and low cost.[27] Wherever there also exist longitudinal

[27] We acknowledge that extending the insurance design outlined in this paper to other settings will require further considerations. First, though AVHRR NDVI series used here have the longest available time series data, several other new NDVI products are available at higher spatial resolution (see http://modis.gsfc.nasa.gov/). Second, while NDVI products appears to work well in the ASAL of northern Kenya, various factors (e.g., cloud mask, altitude, vegetation types) could contribute to geographical variations in effectiveness of NDVI (Box et al 1989). Third, methodologies to transform satellite imagery into representative NDVI data series require careful attention. Ineffective corrections for atmospheric conditions could result in inconsistent reflection of vegetation states. Fourth, as most NDVI products depend on specific satellite platforms, they are prone to temporal discontinuity due to sensor degradation (Tucker et al. 2005). It is thus critical to also establish a back up data series source – calibrated with reasonably high accuracy to the main series – that could substitute for the main series in case of unexpected disruption of data availability. Toward this end, there is particular promise in exploring other new remotely sensed products that are potentially more effective and less dependent on a specific platform, for example, the sensor-independent fraction of Absorbed Photosynthetically Active Radiation (fAPAR) (see http://modis.gsfc.nasa.gov/).

household-level data on an insurable interest (livestock, health status, crop yields, etc.), similar types of index insurance can be designed using the basic techniques outlined here.

A range of implementation challenges nonetheless remain and are the subject of future research. First, the existence of household-level data permit direct exploration of basis risk, looking in particular for systematic patterns so that prospective insurance purchasers can be fully informed as to how well (or poorly) suited the index-based contract might be for their individual case. Chantarat et al. (2010) explores this issue in some detail for this IBLI product.

Second, and relatedly, experience with other index insurance pilots has shown that a carefully designed program of extension to appropriately educate potential clients is necessary for both initial uptake and continued engagement with insurance (Giné et al., 2008; Sarris et al., 2006). Complex index insurance products can be difficult to understand, especially for populations with low levels of literacy and minimal previous experience with formal insurance products. Preliminary field experiments using simulation games played by prospective insurance purchasers show significant promise as a means of both explaining how index insurance products work and generating demand for the product (Lybbert et al. 2010, McPeak et al. 2010).

Third, despite the key advantage of no required costly verifications of individual claims,[28] the infrastructure deficiencies in remote rural areas could still drive up the costs

[28] One might argue for the need to verify the ownership of insured livestock upon signing the contract. Theoretically, this verification is not necessary. As the premium rates are already calibrated to the underlying risk distribution per unit insured (and so one makes payments relative to the insured herd size), whether or not the insured actually owns the livestock or not will not affect the distribution of the insurer's portfolio returns. Practically, however, there may be regulations in the insurance sector that require the demonstration of insurable asset. In Kenya, where a pilot of this product was launched in January 2010, the regulators adopted a wait-and-see approach and allowed sales without verification. If ex-ante verification of insurable asset becomes necessary, one common cost effective practice widely adopted in local developing regions involves the use of community-based mechanism, where the insured livestock unit can be collectively certified by local leaders and government officials.

of product marketing and claims settlement. Development of cost-effective agent networks for reliable, low-cost product marketing and service remains a challenge. In the northern Kenya IBLI case described here, our commercial partners can tap into a network of local agents equipped with electronic, solar rechargeable point-of-sale (POS) devices being extended throughout northern Kenya by a commercial bank working with the central government and donors on a new cash transfer program. These POS devices can be easily configured to accept premium payments and to register indemnity payments for certain insurance contracts. Financial sector interests are attracted by the potential economies of scope involved in introducing another range of products for devices otherwise used purely for government transfers and debit payments.

Fourth, as already mentioned, IBLI underwriters and their commercial partners must make difficult choices in balancing the administrative simplicity and marketing appeal of offering IBLI contracts priced uniformly over space and time (which we termed "unconditional" pricing in the preceding analysis) versus more complex ("conditional") pricing to guard against the possibility of spatial or intertemporal adverse selection. Harmonized pricing is a common practice among Kenyan insurance companies that have ventured into the agricultural sector, using the less risky areas to cross-subsidize premiums for the more risky areas. As indicated in our analysis, the potential intertemporal or spatial adverse selection issues could be greater with index-based products and thus merit attention as this market develops.[29]

These implementation challenges notwithstanding, IBLI shows considerable promise in the pastoral areas of east Africa. By addressing serious problems of covariate

[29] Other common insurance contractual agreements, e.g., no claim bonus, are under consideration among our research community and industry as a way to implicitly impose state-contingent insurance pricing to reduce demand fluctuation due to intertemporal adverse selection.

risk, asymmetric information and high transactions costs that have precluded the emergence of commercial insurance in these areas to date, IBLI offers a novel opportunity to use financial risk transfer mechanisms to address a key driver of persistent poverty. Hence the widespread interest shown in IBLI by government, donors and the commercial financial sector. The design detailed in this paper overcomes the significant challenges of a lack of reliable ground climate data (e.g., from meteorological stations) or seasonal or annual livestock census data, as well as the need to control for the path dependence of the effects of rangeland vegetation on livestock mortality. As the product goes into the field, the true test of IBLI viability and impact will come from monitoring households in the test pilot areas and the financial performance of the institutions involved in offering these new index-based livestock insurance contracts.

References

Adow, M, 2008, Pastoralists in Kenya, Paper Presented at a conference on Climate Change and Forced Migration, the Institute for Public Policy Research, London.

Alderman, H.G. and T. Haque, 2007, Insurance against Covariate Shocks: The Role of Index-based Insurance in Social Protection in Low-Income Countries of Africa, World Bank Working Paper 95, Africa Region Human Development Department, The World Bank, Washington, DC.

Barnett, B.J., C.B. Barrett and J.R. Skees, 2008, Poverty Traps and Index-Based Risk Transfer Products, *World Development*, 36(10): 1766-85.

Barrett, C.B., M.R. Carter and M. Ikegami, 2008, Poverty Traps and Social Protection, Working Paper, Cornell University.

Barrett, C.B., S. Chantarat, G. Gebru, J.G. McPeak, A.G. Mude, J. Vanderpuye-Orgle and A.T. Yirbecho, 2008, Codebook for Data Collected under the Improving Pastoral Risk Management on East Africa Rangelands (PARIMA) Project, Unpublished, Cornell University.

Barrett, C.B., B.J. Barnett, M.R. Carter, S. Chantarat, J.W. Hansen, A.G. Mude, D.E. Osgood, J.R. Skees, C.G. Turvey and M. Neil Ward, 2008, Poverty Traps and Climate Risk: Limitations and Opportunities of Index-Based Risk Financing, *IRI Technical Report* No. 07-02.

Barrett, C.B., P.P. Marenya, J.G. McPeak, B. Minten, F.M. Murithi, W. Oluoch-Kosura, F. Place, J.C. Randrianarisoa, J. Rasambainarivo and J. Wangila, 2006, Welfare

Dynamics in Rural Kenya and Madagascar, *Journal of Development Studies*, 42(2): 248-77.

Bayarjargal, Y., A. Karnieli, M. Bayasgalan, S. Khudulmur, C. Gandush and C.J. Tucker, 2006, A Comparative Study of NOAA-AVHRR-derived Drought Indices using Change Vector Analysis, *Remote Sensing of Environment*, 105: 9-22.

Benedetti, R. and P. Rossini, 1993, On the Use of NDVI Profiles as a Tool for Agricultural Statistics: the Case Study of Wheat Yield Estimate and Forecast in Amilia Romagna, *Remote Sensing of Environment*, 45: 311-26.

Box E, B. Holben and V. Kalb, 1989, Accuracy of the AVHRR Vegetation Index as a Predictor of Biomass, Primary Productivity and Net CO2 Fux, *Vegetatio* 80:71–89

Carter, M.R. and C.B. Barrett, 2006, The Economics of Poverty Traps and Persistent Poverty: An Asset-based Approach, *Journal of Development Studies*, 42(2): 178-99.

Chantarat, S., A.G. Mude, C.B. Barrett and C.G. Turvey, 2010, The Performance of Index Based Livestock Insurance: Ex Ante Assessment in The Presence of a Poverty Trap, Working Paper, Cornell University.

Chantarat, S. and A.G. Mude, 2010, Willingness to Pay for Index Based Livestock Insurance: A Field Experiment from Northern Kenya, Working Paper, Cornell University.

Chantarat, S., C.G. Turvey, A.G. Mude, and. C.B. Barrett, 2008, Improving Humanitarian Response to Slow-Onset Disasters using Famine Indexed Weather Derivatives, *Agricultural Finance Review*, 68(1): 169-95.

Chantarat, S., C.B. Barrett, A.G. Mude, and C.G. Turvey, 2007, Using Weather Index Insurance to Improve Drought Response for Famine Prevention, *American Journal of Agricultural Economics*, 89 (5): 1262-68.

Cole, S., X. Giné, J. Tobacman, P. Topalova, R. Townsend and J. Vickery, 2009, Barriers to Household Risks Management: Evidence from India, Harvard Business School Working Paper 09-116.

de Goncalves, L. G. G., W. J. Shuttleworth, B. Nijssen, E. J. Burke, J. A. Marengo, S. C. Chou, P. Houser, and D. L. Toll, 2006, Evaluation of model-derived and remotely sensed precipitation products for continental South America, *Journal of Geophysical Research*, 111 (D16).

Giné, X., R. Townsend and J. Vickery, 2008, Patterns of Rainfall Insurance Participation in Rural India, *World Bank Economic Review*, 22: 539-66.

Hayes, M.J. and W.L. Decker, 1996, Using NOAA AVHRR Data to Estimate Maize Production in the United States Corn Belt, *International Journal of Remote Sensing*, 17: 3189-200.

Huysentruyt, M., C.B. Barrett and J.G. McPeak, 2009, Understanding Declining Mobility and Interhousehold Transfers Among East African Pastoralists, *Economica*, 76(32): 315-36.

Kamarianakis, Y., H. Feidas, G. Kokolatos, N. Chrysoulakis and V. Karatzias, 2007, Validating remotely sensed rainfall estimates by using nonlinear mixed models and

geographically weighted regression, XIIth Applied Stochastic Models and Data Analysis International Conference, Chania, Greece.

Kogan, F. N., 1990, Remote Sensing of Weather Impacts on Vegetation in Nonhomogeneous Areas, *International Journal of Remote Sensing*, 11: 1405-20.

Kogan, F. N., 1995, Droughts of the Late 1980s in the United States as Derived from NOAA Polar-orbiting Satellite Data, *Bulletin of the American Meteorological Society*, 76: 655-68.

Lybbert, T.J., F. Galarza, J. G. McPeak, C.B. Barrett, S. Boucher, M.R. Carter, S. Chantarat, A. Fadlaoui and A.G. Mude, 2010, Dynamic Field Experiments in Development Economics: Risk Valuation in Morocco, Kenya and Peru, *Agricultural and Resource Economics Review*, 39 (2): 1-17

Lybbert, T.J, C.B. Barrett, S. Desta and D. Layne Coppock, 2004, Stochastic Wealth Dynamics and Risk Management among a Poor Population, *Economic Journal*, 114(498): 750-77.

Mahul, O., and J.R. Skees, 2005, Managing Agricultural Catastrophic Risk at the Country Level: The Case of Livestock Mortality Risk in Mongolia, Working Paper. The World Bank.

McPeak, J.G., S. Chantarat and A.G. Mude, 2010, Explaining Index Based Livestock Insurance to Pastoralists, *Agricultural Finance Review*, 70 (3): 333-52.

McPeak, J.G. and C.B. Barrett, 2001, Differential Risk Exposure and Stochastic Poverty Traps among East African Pastoralists, *American Journal of Agricultural Economics*, 83: 674-79.

Mude, A., C.B. Barrett, J.G. McPeak, R. Kaitho and P. Kristjanson, 2009, Empirical Forecasting of Slow-Onset Disasters for Improved Emergency Response: An Application to Kenya's Arid and Semi-Arid Lands, *Food Policy*, 34(4): 329-39.

Peters, A.J., E.A. Walter-Shea, L. Ji, A. Vina, M. Hayes and M.D. Svoboda, 2002, Drought Monitoring with NDVI-based Standardized Vegetation Index, *Photogrammetric Engineering and Remote Sensing*, 68: 71-75.

Rasmussen, M. S., 1997, Operational yield forecast using AVHRR NDVI data: reduction of environmental and inter-annual variability, *International Journal of Remote Sensing*, 18: 1059-77.

Santos, P. and C.B. Barrett, 2006, Heterogeneous Wealth Dynamics: On the Roles of Risk and Ability, Working Paper, Cornell University.

Santos, P. and C.B. Barrett, forthcoming, Persistent Poverty and Informal Credit, *Journal of Development Economics*.

Sarris, A., P. Karfakis and L. Christiaensen, 2006, Producer demand and welfare benefits of rainfall insurance in Tanzania, FAO Commodity and Trade Policy Research Working Paper No. 18.

Tucker, C. J., J. E. Pinzon, M. E. Brown, D. A. Slayback, E. W. Pak, R. Mahoney, E. F. Vermote, and N. E. Saleous, 2005, An Extended AVHRR 8-km NDVI Data Set

Compatible with MODIS and SPOT Vegetation NDVI Data, *International Journal of Remote Sensing*, 26(14): 4485-98.

Table 1: Descriptive Statistics

Cluster	Location	Annual rain (mm)		NDVI		Herd size (TLU)		Herd composition		Seasonal Mortality Rates, 2000-08					
										Overall		LRLD		SRSD	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Camel	Cattle	Mean	S.D.	Mean	S.D.	Mean	S.D.
Chalbi	North Horr	237	105	0.11	0.03	13	12	10%	3%	9%	15%	6%	9%	11%	20%
	Kalacha	236	105	0.12	0.03	25	10	14%	0%	13%	22%	7%	10%	18%	29%
	Maikona	235	96	0.11	0.04	9	5	11%	2%	10%	11%	8%	7%	13%	15%
Laisamis	Karare	367	159	0.34	0.11	13	9	0%	74%	15%	16%	17%	19%	12%	12%
	Logologo	326	138	0.24	0.12	21	28	5%	31%	8%	14%	10%	16%	6%	12%
	Ngurunit	255	135	0.26	0.08	19	24	7%	19%	8%	11%	11%	14%	5%	8%
	Korr	255	125	0.17	0.07	11	7	5%	3%	11%	13%	13%	12%	9%	14%

Note: Rainfall data from Famine Early Warning System RFE2.0, NDVI from NOAA-AVHRR and livestock data from ALRMP

Table 2: Linear Regression Estimations of Area Average Livestock Mortality

Model	(1) Regime Switching Model		(2) Pooled	(3) Bad Regime	(4) Good Regime	
	$(Czndvi_pos < 0)$	$(Czndvi_pos \geq 0)$		$(Czndvi_pos < 0)$	$(Czndvi_pos \geq 0)$	
Chalbi Model					(i)	(ii)
$Czndvi_pre$	-0.0187***		-0.0077***	-0.0187***	0.0012	
	(0.0051)		(0.0023)	(0.0064)	(0.0032)	
$Czndvi_n$	0.0019		0.0042	0.0019	-0.0086	
	(0.0033)		(0.0033)	(0.0042)	(0.0084)	
$Czndvi_p$	-0.0064		0.0032	-0.0064	0.0030*	
	(0.0087)		(0.0028)	(0.0110)	(0.0016)	
$SRSD$	0.0354		0.1058***	0.0354	0.0356	
	(0.0564)		(0.0342)	(0.0713)	(0.0583)	
$Czndvi_pos$		0.0024				0.0024***
		(0.0018)				(0.0007)
Adjusted R^2	0.5187		0.4421	0.5112	0.2469	0.3419
N	48		48	29	19	19
Laisamis Model						
$Czndvi_pre$	-0.0093***	-0.0003	-0.0029*	-0.0093***	-0.0003	
	(0.0024)	(0.0028)	(0.0016)	(0.0029)	(0.0012)	
$Czndvi_n$	0.0117***	0.0087	0.0133***	0.0117***	0.0087**	
	(0.0022)	(0.0080)	(0.0022)	(0.0027)	(0.0036)	
$Czndvi_p$	-0.0111**	0.0014	0.0006	-0.0111*	0.0014	
	(0.0048)	(0.0024)	(0.0020)	(0.0060)	(0.0011)	
$SRSD$	-0.0446	0.0147	-0.0032	-0.0446	0.0147	

	(0.0299)	(0.0402)	(0.0237)	(0.0368)	(0.0179)
Adjusted R^2	0.6062		0.5436	0.6250	0.4012
N	64		64	38	26

Note: *, **, *** for statistical significance at the 10%, 5% and 1% levels respectively.

Table 3: Out of Sample Testing of Indemnity Payment Error

Cluster	Strike	Proportion of Sample		
		Correct decision	Type I error	Type II error
Chalbi (N=16)	10%	0.75	0.00	0.25
	15%	0.88	0.13	0.00
	20%	0.75	0.25	0.00
	25%	0.88	0.13	0.00
	30%	0.88	0.13	0.00
Laisamis (N=16)	10%	1.00	0.00	0.00
	15%	1.00	0.00	0.00
	20%	0.75	0.00	0.25
	25%	0.75	0.00	0.25
	30%	0.75	0.00	0.25

Note: Out-of-sample errors are based on PARIMA data, which include 4 seasonal area mortality data from long rain long dry 2000 to that of 2002 in North Horr and Kargi (Dirib Gombo and Logologo) in Chalbi (Laisamis) cluster.

Table 4: Simulated Shares of Household's Insurable Losses Explained by Mortality Index

Strike	Frequency of true loss beyond strike	Frequency of IBLI indemnity payment when true loss was beyond strike	Share (%) of Insurable Losses Explained by Mortality Index	
(M^*)	$Pr(M_{ils} > M^*)$	$Pr\left(\widehat{M}(ndvi_{ls}) > M^* \mid M_{ils} > M^*\right)$	when $M_{ils} > M^*$ and $\widehat{M}(ndvi_{ls}) > M^*$	when $M_{ils} > M^*$
10%	22%	82%	25%	21%
20%	13%	40%	59%	23%
30%	6%	54%	73%	39%

Note: 500 households are simulated for 4 locations based on 2000-2 PARIMA panel data and 1982-2008 NDVI data. See Chantarat et al. 2010 for more details. Note that column 5 is the product of columns 3 and 4.

Table 5: Unconditional Vs. Conditional Fair Annual Premium Rates

	Indemnity Payment Rate (% of insured TLU value)									
	Mean (actuarially fair premium rates)					S.D.				
Strike	10%	15%	20%	25%	30%	10%	15%	20%	25%	30%
Unconditional										
Chalbi	8.7%	5.2%	2.7%	1.1%	0.3%	9.5%	6.5%	3.8%	2.0%	0.8%
Laisamis	5.5%	3.1%	1.4%	0.5%	0.1%	5.5%	3.1%	1.4%	0.5%	0.1%
Conditional on observed good pre-condition										
Chalbi	5.1%	3.1%	1.7%	0.7%	0.2%	6.9%	5.1%	3.4%	1.9%	0.7%
Laisamis	1.3%	0.5%	0.1%	0.0%	0.0%	3.1%	1.3%	0.2%	0.0%	0.0%
Conditional on observed bad pre-condition										
Chalbi	11.2%	6.6%	3.4%	1.3%	0.4%	10.5%	7.2%	4.4%	2.4%	1.1%
Laisamis	8.8%	5.2%	2.4%	0.9%	0.2%	9.3%	6.5%	4.2%	2.2%	0.7%

Note: Cluster-specific statistics are based on equally weighted average of location-specific payment rates. This pricing thus is based on the assumption that contracts are priced per cluster while indemnity payments are made per coverage location. Mean and S.D. are calculated over all possible combinations of 2 consecutive coverage seasons during historical NDVI period.

Figure 1: Clustered Sites in Marsabit, Northern Kenya

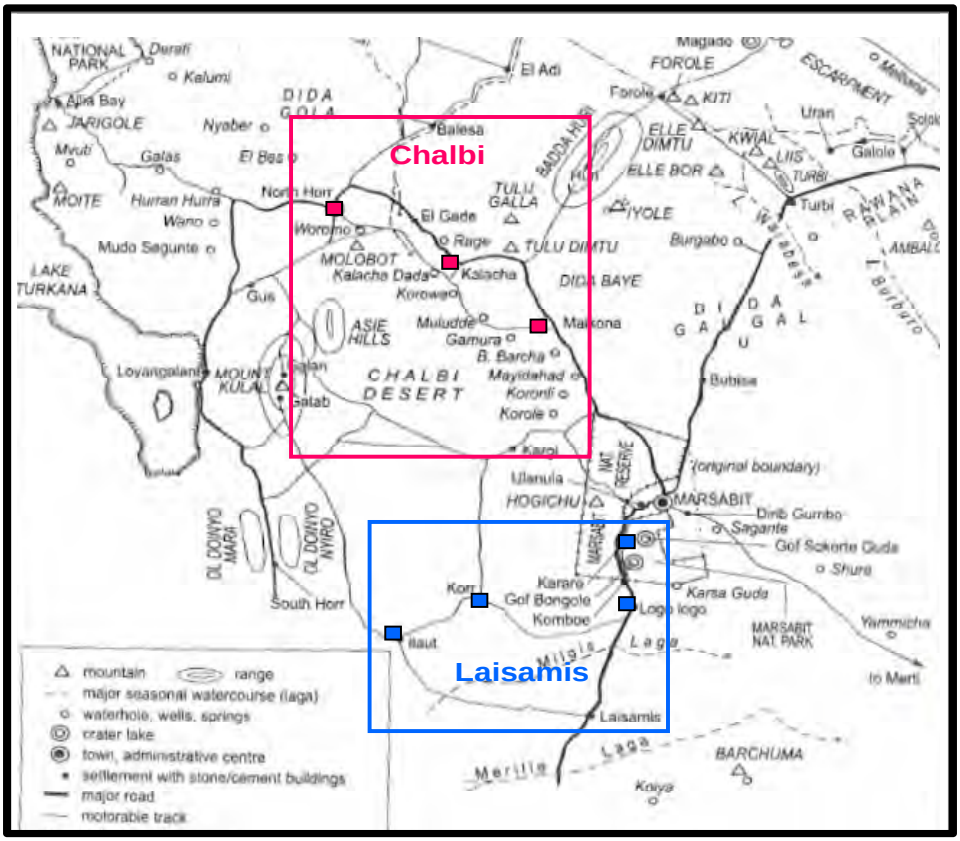


Figure 2: Seasonal TLU Mortality Rate by Clusters

Figure 3: NDVI and zndvi for Locations in Marsabit, by Clusters

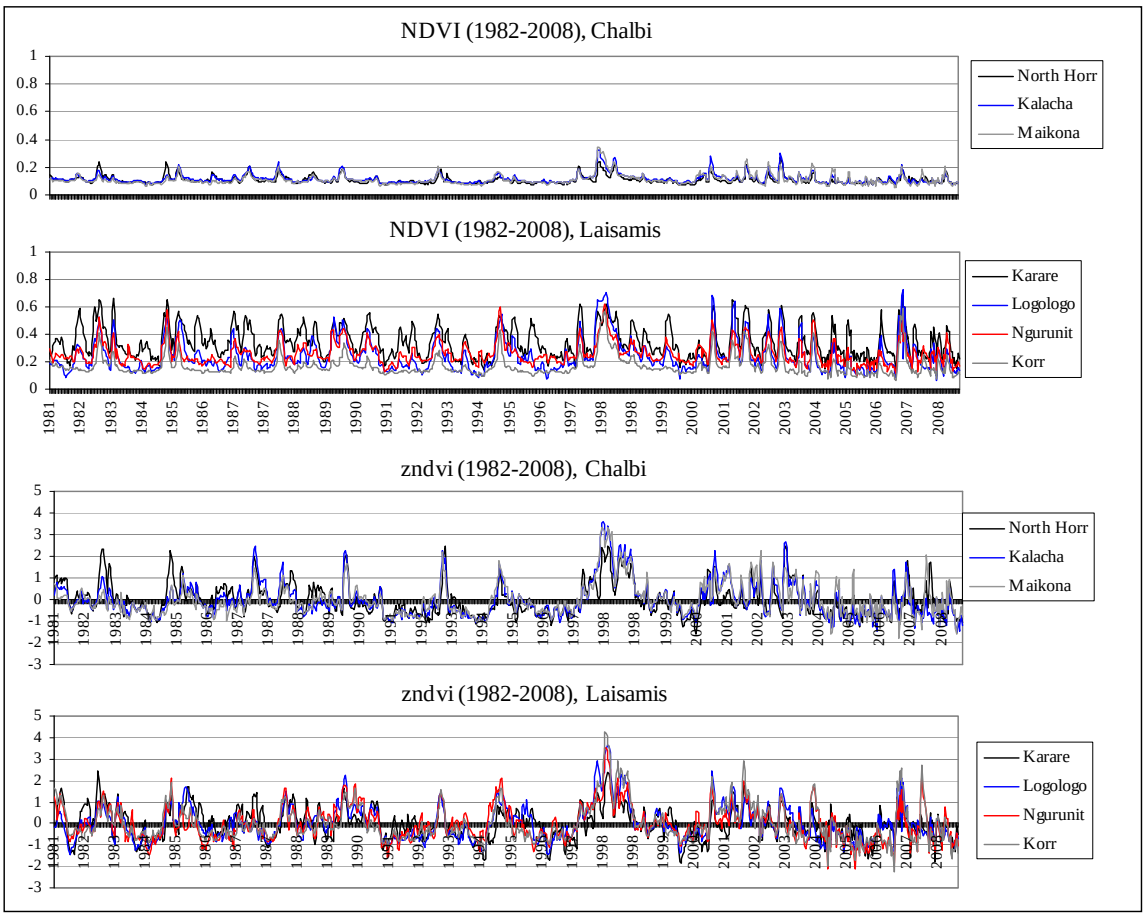
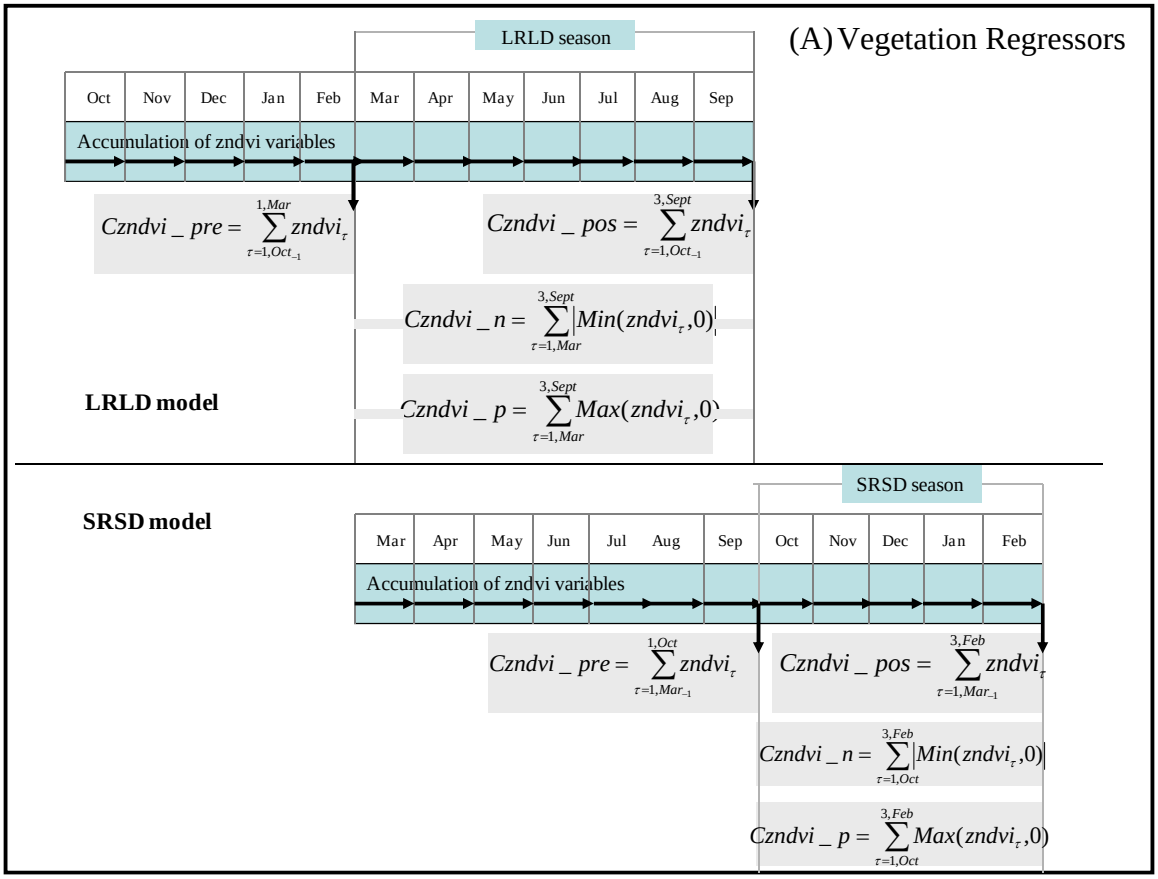


Figure 4: Temporal Structure of Vegetation Regressors and IBLI Contract



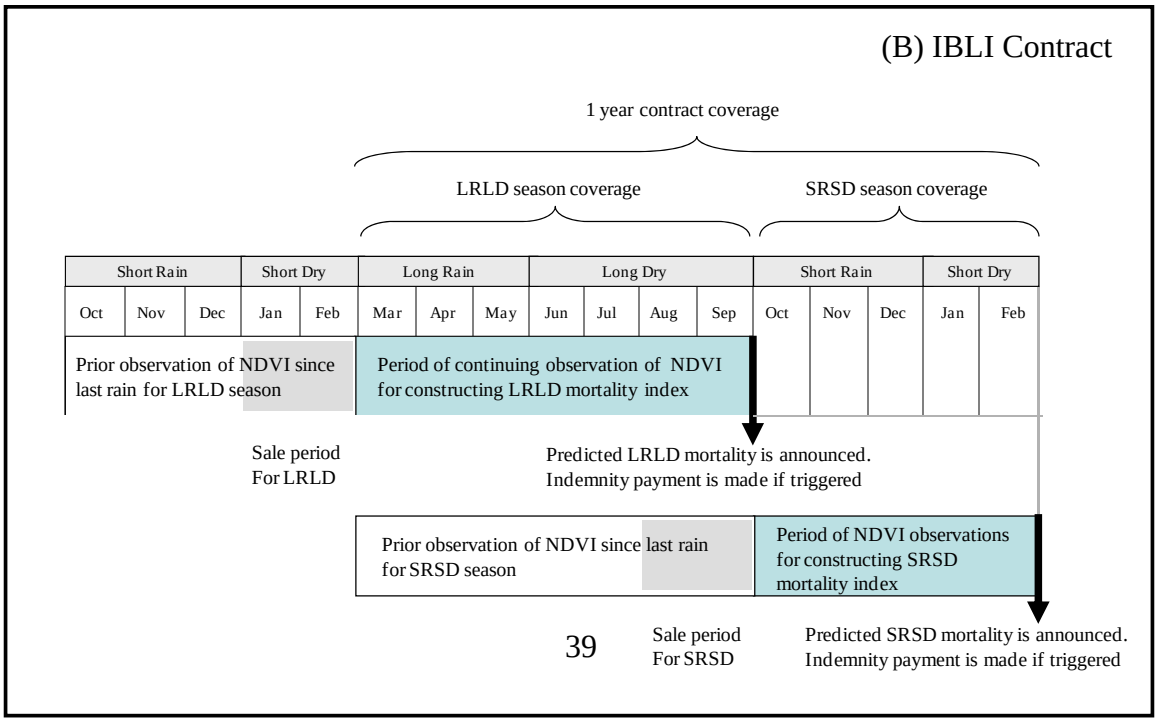


Figure 5: Empirical Distributions of Predicted TLU Mortality Indices

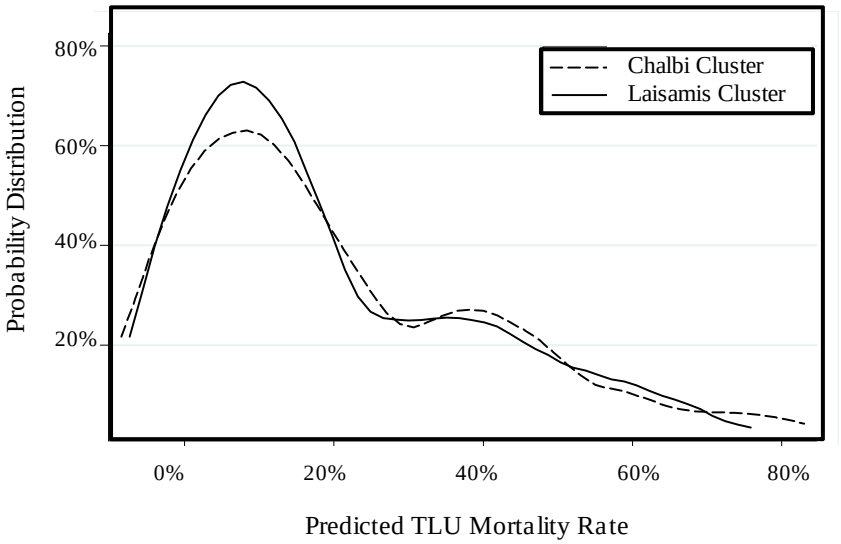
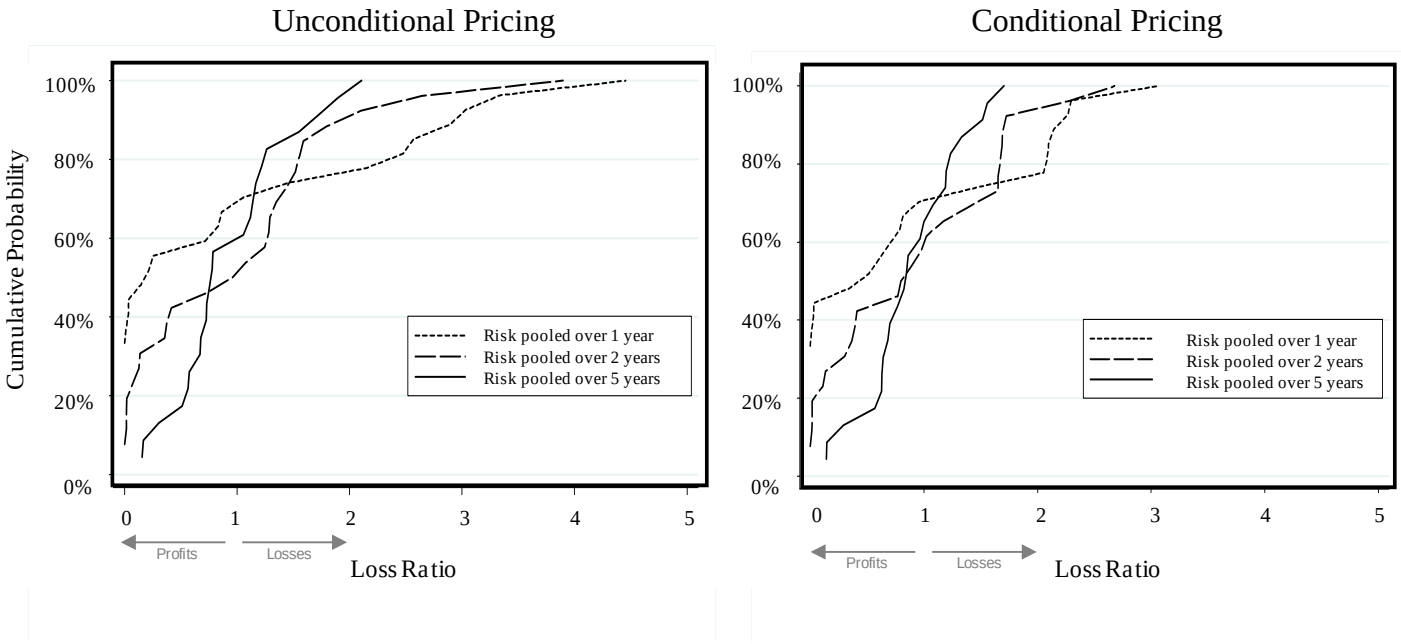


Figure 6: Loss Ratio Cumulative Distributions, by Pricing and Years of Risk Pooled (15% Strike)



Appendix Table A1: Descriptive Statistics for Vegetation Index Regressors and Area-Average Seasonal Mortality, by Location and Regime (2000-2008)

Cluster/ Location	Variable	Overall				SRSD Season		LRLD Season		Good Year Czndvi_pos>=0		Bad Year Czndvi_pos<0		% Bad-Climate Regime
		Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Chalbi	Mortality rate	0.1	0.2	0.0	0.7	0.1	0.2	0.1	0.1	0.0	0.1	0.1	0.2	
(Pooled)	Czndvi_pos	-1.5	15.9	-26.3	25.9	-1.8	15.7	-1.2	16.5	15.8	7.4	-12.9	7.3	60%
	Czndvi_pre	-0.7	9.9	-19.6	21.8	-0.3	13.2	-1.1	5.1	8.6	7.4	-6.8	5.7	
	Czndvi_n	6.4	4.6	0.1	18.6	5.2	3.0	7.6	5.6	2.5	1.6	8.9	4.1	
	Czndvi_p	5.5	6.0	0.0	21.4	3.6	2.7	7.4	7.7	9.9	7.0	2.6	2.7	
North Horr	Mortality rate	0.1	0.2	0.0	0.6	0.1	0.2	0.1	0.1	0.0	0.0	0.2	0.2	
	Czndvi_pos	-4.8	14.3	-26.2	17.4	-4.9	14.3	-4.7	15.3	9.0	5.7	-15.5	7.9	56%
	Czndvi_pre	-2.5	9.5	-19.6	18.3	-2.6	12.9	-2.4	5.2	5.0	6.7	-8.4	7.0	
	Czndvi_n	6.9	5.0	1.6	18.6	5.4	2.9	8.4	6.4	3.3	1.3	9.7	5.1	
	Czndvi_p	4.4	5.3	0.0	20.7	3.0	2.5	5.8	7.0	7.3	6.6	2.2	2.7	
Kalacha	Mortality rate	0.1	0.2	0.0	0.7	0.2	0.3	0.1	0.1	0.0	0.0	0.2	0.2	
	Czndvi_pos	-1.5	17.9	-26.3	25.9	-2.1	18.6	-0.9	18.5	19.3	5.9	-14.0	7.4	63%
	Czndvi_pre	-0.6	10.9	-16.5	21.8	-0.4	15.0	-0.8	5.5	10.2	8.4	-7.1	5.9	
	Czndvi_n	6.6	5.0	0.6	16.3	5.3	3.7	7.9	5.9	2.1	1.5	9.4	4.2	
	Czndvi_p	5.6	6.7	0.0	21.4	3.5	2.7	7.7	8.9	11.3	7.9	2.2	2.4	
Maikona	Mortality rate	0.1	0.1	0.0	0.4	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	
	Czndvi_pos	1.8	15.7	-17.4	24.4	1.5	15.3	2.0	17.1	20.3	4.5	-9.3	5.8	63%
	Czndvi_pre	1.0	9.5	-10.8	18.7	2.1	12.9	0.0	5.0	11.2	6.7	-5.1	4.0	
	Czndvi_n	5.6	4.0	0.1	11.1	4.8	2.7	6.4	5.0	1.9	2.0	7.8	3.1	
	Czndvi_p	6.3	6.1	0.0	19.9	4.2	3.0	8.5	7.7	11.4	6.8	3.3	3.0	
Laisamis	Mortality rate	0.1	0.1	0.0	0.6	0.1	0.1	0.1	0.1	0.0	0.0	0.1	0.2	
(Pooled)	Czndvi_pos	-3.5	16.5	-35.3	34.9	-3.8	16.7	-3.2	16.6	12.9	9.0	-14.7	9.7	59%
	Czndvi_pre	-1.9	10.1	-20.3	23.0	-1.7	12.1	-2.2	7.8	6.0	7.9	-7.4	7.7	
	Czndvi_n	6.7	5.1	0.0	19.6	5.8	4.1	7.7	5.9	2.5	2.1	9.6	4.6	
	Czndvi_p	4.8	5.8	0.0	24.1	3.4	4.3	6.3	6.8	9.3	5.7	1.8	3.6	
Karare	Mortality rate	0.1	0.2	0.0	0.6	0.1	0.1	0.2	0.2	0.1	0.0	0.2	0.2	
	Czndvi_pos	-5.8	12.7	-26.8	19.1	-6.2	13.8	-5.4	12.5	7.3	7.4	-13.6	7.5	63%
	Czndvi_pre	-3.1	7.8	-16.0	12.3	-3.4	8.5	-2.7	7.7	2.5	6.2	-6.4	6.9	
	Czndvi_n	6.5	4.4	0.3	16.3	6.0	4.4	7.0	4.7	2.4	1.2	8.9	3.8	
	Czndvi_p	3.4	3.7	0.0	13.4	2.9	3.1	3.9	4.4	6.8	4.1	1.3	1.2	
Logologo	Mortality rate	0.1	0.1	0.0	0.4	0.1	0.1	0.1	0.2	0.0	0.0	0.1	0.2	
	Czndvi_pos	-2.5	17.4	-26.3	26.5	-2.7	19.3	-2.3	16.5	13.1	7.5	-18.1	5.6	50%
	Czndvi_pre	-1.4	10.5	-14.9	17.2	-1.1	13.0	-1.8	8.3	6.1	8.7	-8.9	5.7	
	Czndvi_n	6.2	4.9	0.2	14.6	5.4	4.0	7.0	5.9	2.3	1.4	10.1	3.9	
	Czndvi_p	4.8	6.3	0.0	18.7	3.6	4.6	6.1	7.7	9.3	6.3	0.4	0.5	
Ngurunit	Mortality rate	0.1	0.1	0.0	0.4	0.1	0.1	0.1	0.1	0.0	0.0	0.1	0.1	
	Czndvi_pos	-4.3	16.8	-35.3	22.8	-4.7	16.8	-3.9	17.9	11.8	7.7	-14.0	12.6	63%
	Czndvi_pre	-2.3	10.2	-20.3	16.1	-2.1	13.1	-2.6	7.2	5.4	6.2	-7.0	9.5	
	Czndvi_n	7.0	6.0	0.2	19.6	5.7	4.8	8.3	7.1	2.5	2.5	9.7	5.8	
	Czndvi_p	4.6	5.0	0.0	17.1	2.7	2.7	6.6	6.2	8.7	4.6	2.2	3.6	
Korr	Mortality rate	0.1	0.1	0.0	0.4	0.1	0.1	0.1	0.1	0.0	0.0	0.2	0.2	
	Czndvi_pos	-1.4	19.8	-30.1	34.9	-1.5	19.3	-1.3	21.6	19.2	11.4	-13.7	11.4	63%
	Czndvi_pre	-1.0	12.3	-17.7	23.0	-0.2	15.3	-1.7	9.5	9.9	9.5	-7.5	8.8	
	Czndvi_n	7.2	5.5	0.0	17.2	6.0	4.2	8.4	6.6	2.9	3.4	9.8	4.9	
	Czndvi_p	6.5	7.7	0.0	24.1	4.3	6.4	8.6	8.7	12.2	7.0	3.0	6.0	

Appendix Table A2: Out of Sample Forecasting Errors

Error Magnitude (absolute value)	Proportion of Sample	
	Chalbi (N=8)	Laisamis (N=8)
Under prediction		
< 5%	0.13	0.50
5-10%	0.25	0.25
10-15%	0.00	0.00
15-20%	0.00	0.00
20-25%	0.00	0.00
>25%	0.00	0.13
Over prediction		
< 5%	0.38	0.13
5-10%	0.13	0.00
10-15%	0.00	0.00
15-20%	0.00	0.00
20-25%	0.00	0.00
>25%	0.13	0.00
Total	1.00	1.00

Note: Out-of-sample errors are based on PARIMA data, which include 4 seasonal area mortality data from long rain long dry 2000 to that of 2002 in North Horr and Kargi (Dirib Gombo and Logologo) in Chalbi (Laisamis) cluster. Mean and variance tests are performed to compare the distributions between these out-of-sample errors and the predictive error from each cluster-specific model. In all cases, t and F statistics cannot reject the null hypotheses of equal mean/variance, resulting in $t(54) = 0.5992$ and $F(47,7) = 1.3164$ for Chalbi cluster; $t(70) = -1.3326$ and $F(63,7) = 0.9972$ for Laisamis cluster.

Appendix Table A3: Mean Reinsurance Rates for 100% Stop Loss Coverage

Strike	Stop-loss Reinsurance Coverage at 100% of Pure Premium			
	Unconditional Premium		Conditional Premium	
	Mean	S.D.	Mean	S.D.
10%	49%	83%	32%	53%
15%	53%	95%	35%	60%
20%	56%	108%	36%	66%
25%	59%	134%	42%	85%
30%	68%	162%	49%	115%