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

Abstract

This paper describes a novel effort at developing index-based insurance for location-averaged livestock mortality as a means to fill an important void in the risk management instruments available to protect the main asset of pastoralists in the arid and semi-arid lands of Kenya, where insurance markets are effectively absent and uninsured risk exposure is a main cause of the existence of poverty traps. We describe the detailed methodology in designing such insurance contract with the underlying index uniquely constructed off explicit statistical predictions established using longitudinal observations of household-level herd mortality, fit to high quality, objectively verifiable remotely sensed vegetation data not manipulable by either party to the contract and available at low cost and in near-real time. The resulting index performs very well out of sample, both when tested against other complementing 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. We describe contract pricing and potential risk exposures of the underwriter using a rich time series of satellite-based vegetation data available from 1982-present. And finally, implementation opportunities and challenges are discussed to spur the product's pilot potential.

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

1. Introduction

Uninsured risk has long been recognized as a serious obstacle to poverty reduction in poor agrarian nations. In order to limit risk exposure, risk averse poor households often select low-risk, low-return asset and activity portfolios that trade off growth potential and expected current income for a lower likelihood of catastrophic outcomes (Eswaran and Kotwal 1989, 1990; Rosenzweig and Binswanger 1993; Morduch 1995; Zimmerman and Carter 2003; Dercon 2005; Carter and Barrett 2006; Elbers et al. 2007). Furthermore, because risk exposure leaves lenders vulnerable to default by borrowers, uninsured risk commonly limits access to credit, especially for the poor who lack collateral to guarantee loan repayment. And if an asset used to secure the loan is itself at risk, lack of insurance can even compromise the opportunities afforded through collateral. The combination of conservative portfolio choice induced by risk aversion and credit market exclusion due to uninsured default and asset risk helps to perpetuate poverty.

Rural populations in low-income countries commonly face much uninsured risk because covariate risk, asymmetric information, and high transaction costs preclude the emergence of formal insurance markets. Covariate risk is a major cause of insurance market failures in low-income countries as spatially-correlated catastrophic losses can easily exceed the reserves of an insurer, leaving policyholders unprotected (Besley 1995). Such covariate risk exposure explains why crop insurance policies are generally available only where governments take on much of the catastrophic risk exposure faced by insurers (Binswanger and Rosenzweig 1986; Miranda and Glauber 1997). Meanwhile, familiar asymmetric information problems – adverse selection and moral hazard – pose a serious challenge to commercial insurance provision. Finally, the transaction costs of contracting and claims verification are much higher in rural areas than in cities due to limited transportation, communications and legal infrastructure. While informal insurance through social networks can address many of the asymmetric information and transactions costs problems, these too are typically overwhelmed by covariate risk. The end result is widespread insurance market failure.

Index insurance based on cumulative rainfall, cumulative temperature, area average yield, area livestock mortality, and related indices have recently been developed to try to address otherwise-uninsured losses caused by various natural perils in low-income countries (Recently reviewed by Skees and Collier 2008; Barrett et al. 2008; Alderman and Haque 2007). Unlike traditional insurance, which makes indemnity payments to compensate for individual losses, index insurance makes payments based on realizations of an underlying – transparent and objectively measured – index (e.g. amount of rainfall or cumulative temperature over a season, or area-average livestock mortality) that is strongly associated with insurable loss.

An index insurance contract has three main components. First, it requires a well-defined index and an associated strike level that triggers an insurance payout. The index must be highly correlated with the aggregate loss being insured, and based on data sources not easily manipulated by either the insured or the insurer, and with adequate, reliable historical data to estimate the probability distribution of the index for proper pricing and risk exposure analysis. Second, it requires well-defined spatiotemporal coverage with premium pricing specific to that place and period. Third, the contract requires a clear payout timing and structure to all covered clients conditional on the index reaching the contractually specified strike level.

The benefits to such a contract design are several and especially appropriate to rural areas of developing countries where covariate risk, asymmetric information and high transactions costs render conventional insurance commercially unviable. By construction, the index captures covariate risk since it reflects the average (e.g., yield, mortality) or shared (e.g., rainfall, temperature) experience of the insurable population. If this covariate risk can be reinsured or securitized, locally-covariate risk can be transferred into a broader (international) risk pool where it is weakly or uncorrelated with the returns to other financial assets (Hommel and Ritter 2005; Froot 1999). Furthermore, index insurance contracts avoid the twin asymmetric information problems of adverse selection (hidden information) and moral hazard (hidden behavior) because the indices are not individual-specific; they explicitly target – and transfer to insurers – covariate risk within the contract place and period. Finally, insurance companies and insured clients need only monitor the index to know when a claim is due and indemnity payments must be made. They do not need to verify claims of individual losses, which can substantially reduce the transactions costs of monitoring and verification of the insurance contracts.

These gains come at the cost of basis risk, which refers to the imperfect correlation between an insured's potential loss experience and the behavior of the underlying index on which the index insurance payout is based. A contract holder may experience the type of losses insured against but fail to receive a payout if the overall index is not triggered. Conversely, while the aggregate experience may result in a triggered contract, some insured individuals may not have experienced losses yet still receive payouts. The tradeoff between basis risk and reductions in incentive problems and costs is thus a critical determinant of the effectiveness of index insurance products.

Although the overwhelming majority of insurance worldwide covers asset risk, to date almost all retail-level IBRTPs in developing countries have been designed to insure stochastic income streams, primarily crop income plagued by weather risk. This paper demonstrates the potential of index-based insurance contracts to manage livestock asset risk among pastoral communities in northern Kenya, what we call Index-Based Livestock Insurance (IBLI). Mongolia has the only current example of an IBLI product. Offered commercially to individual herders by private insurance companies, the Mongolian IBLI product is based on area average mortality collected by a national census; the insurers are then reinsured through a contingent debt facility with the national government and the World Bank Group (Alderman and Haque 2007; Mahul and Skees 2005, 2006). Concerns exist, however, because of both the cost and timeliness of collecting accurate annual census data, and the capacity of government – an interested party to the contracts – to manipulate the livestock mortality data.

Mongolian-type IBLI is infeasible in our setting, as government does not routinely and reliably collect livestock mortality data. But advances in remote sensing make it possible to design index insurance based on increasingly precise, inexpensive, objectively verifiable, real-time estimates of key observable geographic variables. Because grazing systems ultimately revolve around forage availability, we use the increasingly popular remotely sensed Normalized Differential Vegetation Index (NDVI), an indicator of vegetative cover widely used in drought monitoring programs and early warning systems in Africa (Sung and Weng, 2008), to predict livestock mortality. NDVI-based index insurance contracts have recently emerged. The United States Department of Agriculture's Risk Management Agency now issues pasture insurance based on both rainfall and NDVI indices. The Millennium Villages Project (Earth Institute at Columbia University and UNDP) in partnership with Swiss Re has just developed a drought index insurance program in a number of rural African villages. Preliminary results show that NDVI reliably signals most major drought years in regions with high seasonal NDVI variance, such as the semi-arid Sahel region of Africa (Ward et al. 2008).

We make three important innovations in this paper. First, we explain the design of the first index insurance contract for developing countries designed based on household-level panel data measuring asset loss experiences. Second, we demonstrate how one can build index insurance contracts off explicit statistical predictions of the variable of intrinsic insurable interest – in our case, livestock mortality – rather than relying only on implicit relationships between that variable and measurable proxies (e.g., NDVI, rainfall, temperature). Third, our data permit unprecedented out-of-sample performance testing of these contracts. The resulting contract has attracted significant financial sector interest in the region and will launch commercially in early 2010.

The remainder of the paper is organized as follows. Section 2 describes the northern Kenya context. Section 3 explains the livestock mortality and remote sensing vegetation data available. Section 4 details the IBLI contract design, the construction of key variables and the estimation methods employed. Section 5 reports and evaluates the performance of the estimated livestock mortality models that underpin the IBLI contract. Section 6 discusses contract pricing and risk exposure. Section 7 concludes with a discussion of implementation challenges for this and similar index insurance products.

2. The Northern Kenya Context

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 therefore perhaps 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 beyond a critical threshold – typically 8-16 tropical livestock units (TLUs)[1] – tend to tip a household into collapse into destitution (Barrett et al., 2006; Lybbert et al., 2004; McPeak and Barrett, 2001). Indeed, uninsured risk appears a primary cause of the existence of poverty traps among east African pastoralists (Santos and Barrett 2008).

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 – long dry spell runs March-May and June-September, respectively. 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 interhousehold transfers of a breeding cow; but these schemes cover less than ten percent of household losses, on average, do not include everyone and are generally perceived as in decline (Lybbert et al. 2004, Santos and Barrett 2008, Huysentruyt et al. 2009). 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 vast majority of intertemporal variability in herd sizes is biologically regulated, due to

[1] 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.

births and deaths (McPeak and Barrett 2001, Lybbert et al. 2004). Thus most livestock mortality risk remains uninsured at household level.

Meanwhile, most herd losses occur in droughts as covariate shocks affecting many households at once, sparking a humanitarian emergency. 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 means of livestock mortality and drought risk management, including the development of viable financial risk transfer products. The most recent parliamentary campaign in Kenya included widespread, highly publicized promises by prominent politicians to develop livestock insurance for the northern Kenyan ASAL.

3. Data description

The northern Kenya IBLI contract is designed using combination of household-level livestock mortality data collected monthly since 1996 in various 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 computed reliable at high spatial resolution (8 km^2 grids) and consistent quality from satellite-based Advanced Very High Resolution Radiometer (AVHRR) measurement since 1981.[2] 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 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 contract design is, to the best of our knowledge, unique.

We focus specifically on what was until recently Marsabit District, where the ALRMP data are most complete and reliable, offering monthly household survey data from January 2000 to January 2008 in 7 locations in Marsabit[3] It is thus possible to construct location-specific seasonal herd mortality rate for each location for long rain-long dry seasons (the period from March-September) and short rain-short dry seasons (from October-February), providing a minimally adequate sample size of 112 location-and-season specific observations.

[2] The United States National Oceanic and Atmospheric Administration satellite-based Advanced Very High Resolution Radiometer (AVHRR) collects the data that are then processed by the Global Inventory Monitoring and Modeling Studies 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 NDVI are available at http://earlywarning.usgs.gov/adds/readme.php?symbol=nd.

[3] In 2008 the District was broken into three new Districts: Chalbi, Laisaimis and Marsabit.

As sample households vary by survey round, we rely on monthly location average herd mortality, $\overline{H}_{mort,m}$, to construct seasonal location average mortality rate, M_{ls}, as according to

$$(1) \qquad M_{ls} \equiv \frac{\sum_{m \in s} \overline{H}_{mort,m}}{\underset{m \in s}{Max}\left(\overline{H}_{beg,m}\right)}$$

where $\overline{H}_{beg,m}$ is monthly location average beginning herd size and season *s* represents either the LRLD (March-September) or 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 monthly beginning herd size 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 peoples.

Table 2 reports mortality rates by location.[4] 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 correlated within the same cluster (0.80-0.95), while correlations between clusters are less. As Figure 2 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. The frequency of area average mortality rates exceeding 10% is approximately 33% (a 1-in-3 year event) for both Chalbi and Laisamis. However, the probability of herd mortality exceeding 20% (30%) is approximately 15% (9%) for Chalbi in contrast to 19% (14%) for Laisamis, while the proportion of extreme herd mortality exceeding 50% is approximately 6% for Chalbi in contrast to only 2% for Laisamis.

During the same period as the ALRMP data collection, the PARIMA project undertook an intensive household panel survey in northern Kenya and southern Ethiopia. Two locations – Logologo and North Horr – exist in both household data sets. Although the shorter duration (2000-2 only) of the PARIMA survey provides insufficient observations to estimate the IBLI contract model (described below), we can use the

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

higher quality PARIMA 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 appear suitable for out-of-sample evaluation of IBLI contracts based on the ALRMP herd mortality data and NDVI measures.

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 surveys of the sort used for computing area average mortality, the index used in the developing world's other IBLI contract, in Mongolia. The ALRMP 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. Rainfall estimates based on satellite-based remote sensing remain controversial within climate science.[5]

NDVI is a satellite-derived indicator of the amount and vigor of vegetation, based on the observed level of photosynthetic activity (Tucker 2005). Images of NDVI are therefore sometimes referred to as "greenness maps." Because pastoralists routinely graze animals beyond the 8 km^2 resolution of the data, we average observations for each period within a grazing range defined as the rectangle that encompasses the residential locations and water points used by herders in each community, plus 0.02 degrees (about 10 kilometers) in each direction.[6] In unobserved bad years, pastoralists may travel further

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[5] 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).

[6] To define location boundary for the three locations with available GPS for water points, we first identified GPS bound on each side of the rectangular among all the available GPS points and extended 0.02 degree (around 10 km.) to each side of the GPS bound. And thus, eastbound of the rectangular = max (the available GPS Y-coordinate) +0.02, westbound = min (the available GPS Y-coordinate) - 0.02, northbound of the rectangular = max (the available GPS X-coordinate) +0.02 and southbound = min (the available GPS

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 with previous time periods in order to detect anomalous conditions and to anticipate drought (Bayarjargal et al. 2006; Peters et al. 2002) and have now been used by many studies that apply remote sensing data to drought management (Benedetti and Rossini 1993; Hayes and Decker 1996; Kogan 1990, 1995; Rasmussen 1997).

4. Designing Vegetation Index Based Livestock Insurance for Northern Kenya

Recent research finds that humanitarian emergencies in this region – indicated by widespread severe child malnutrition – can be predicted reasonably accurately several months in advance. Furthermore, the recent droughts with dire consequences – in 1997, 2000 and 2005-06 – were all characterized not only by low rainfall, but also by the spatial extent and duration of the low rainfall event and its effects on rangeland conditions (Chantarat et al. 2007; Mude et al. forthcoming). The apparent predictability of these episodes motivates our approach to IBLI design based on predicted livestock mortality.

In order to confirm the appropriateness of our approach to IBLI contract design, 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 et al. (2009c) and Lybbert et al. (2009) describe those studies, which confirmed (i) pastoralists' keen interest in an IBLI product, (ii) their comprehension of the basic features of the IBLI product we explain below, and (iii) significant willingness to pay for the product at commercially viable premium rates. Pastoralists in these communities worry about livestock loss, clearly associated this with pasture conditions, and readily accept the idea that greenness measures gathered from satellites ("the stars that move at night" in local dialectics) can reliably signal drought and significant livestock mortality. With demand for an IBLI product established, we proceed now with the specifics of contract design.

4.1 Contract design

We design a seasonal contract covering the LRLD or SRSD season, each encompassing a rainy and dry season pair. Insurance contracts are sold (for approximately two months) just before the start of the rainy season and are assessed at the end of the dry period to determine whether indemnity payments are to be made. Contracts are specified per tropical livestock unit (TLU) at a pre-agreed value per TLU. Pastoralist clients choose the total livestock value to insure, pay the associated premium to the insurance broker and receive indemnity payments proportionate to their IBLI coverage in the event of a payout. The contract is specific at the location level, based on the predicted mortality rate as a function of the vegetation index specific to the grazing range of that location. It is also possible to design a one-year contract covering two consecutive seasonal contracts, consisting of two potential trigger payments per year (at the end of each dry season),

X-coordinate) - 0.02. The result for each location is a rectangle boundary containing all the common water points, GPS of representative households in the ALRMP survey and the current household-level survey in each location.

although we focus here on the seasonal contracts. Figure 3 depicts the temporal structure of the IBLI contract.

The index on which the insurance contract is written is the predicted area average mortality rate, defined as a function of the NDVI-based vegetation index. Because NDVI data are available in real time, the predicted mortality index can be updated continuously over the course of the contract period. We express the index in terms of percentage predicted mortality instead of NDVI in order to expressly link the index to the insurable interest of contract holders.

The livestock mortality index that underpins IBLI is designed as follows. Write the realized aggregate TLU mortality rate of pastoralist household i in location l over season s as

(2) $$M_{ils} = \overline{M}_{il} + \beta_i\left(M_{ls} - \overline{M}_l\right) + \varepsilon_{ils}$$

where $\overline{M}_{il}$ reflects household i's long-term average mortality rate, M_{ls} is the area average mortality rate at location l over season s, $\overline{M}_l$ 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 necessary one.

IBLI insures only the covariate component of M_{ils} that is associated with the observable vegetation index. The area average livestock mortality rate, M_{ls}, can be orthogonally decomposed into the systematic risk associated with the vegetation index and the risk driven by other factors:

(3) $$M_{ls} = M\left(X(ndvi_{ls})\right) + \varepsilon_{ls}$$

where $X(ndvi_{ls})$ represents a transformation of the average NDVI observed over season s in location $l, ndvi_{ls}$ – which we discuss below – $M(\cdot)$ represents the statistically predicted relationship between $X(ndvi_{ls})$ and M_{ls}, and ε_{ls} is the idiosyncratic components of area average mortality that is not explained by $X(ndvi_{ls})$ – i.e., location-specific basis risk. We predict area average mortality from observations of $ndvi_{ls}$, specific to each location l and season s, as:

(4) $$\hat{M}_{ls} = M\left(X(ndvi_{ls})\right),$$

which serves as the underlying index for insurance contract. There are thus two sources of basis risk: (i) the household's idiosyncratic losses that are uncorrelated with area average losses according to (2) and (ii) area average mortality losses that are not correlated with the vegetation index, according to (3).

IBLI then functions like a put option on predicted area average mortality rate. The seasonal contract pays an indemnity beyond the contractually-specified strike mortality level, M_l^*, conditional on the realization of $\hat{M}_{ls}$ according to:

$$\text{(5)} \qquad \Pi_{ls}\left(\hat{M}_{ls} \mid M_l^*, TLU, P_{TLU}\right) = Max\left(\hat{M}_{ls} - M_l^*, 0\right) \times TLU \times P_{TLU}$$

where TLU is the TLU insured and P_{TLU} is the pre-agreed value of 1 TLU, so their product reflecting the insured value. The expected insurance payout and hence the actuarially fair premium for this contract insuring $TLU \times P_{TLU}$ of totally livestock value can be written as

$$\text{(6)} \qquad P_{ls}\left(\hat{M}_{ls} \mid M_l^*, TLU, P_{TLU}\right) = E\left(Max\left(\hat{M}_{ls} - M_l^*, 0\right)\right) \times TLU \times P_{TLU}$$

where $E(\cdot)$ is the expectation operator taken over the distribution of the vegetation index and so we can write $p_{ls}\left(\hat{M}_{ls} \mid M_l^*\right) = E\left(Max\left(\hat{M}_{ls} - M_l^*, 0\right)\right)$ as the actuarially fair premium rate quoted as percentage of total value of livestock insured.

Similarly, total insurance payout at the end of year t for a one-year (two season) contract can be written as:

$$\text{(7)} \qquad \Pi_{lt}\left(\hat{M}_{ls\in t} \mid M_l^*, TLU, P_{TLU}\right) = \sum_{s\in t} Max\left(\hat{M}_{ls} - M_l^*, 0\right) \times TLU \times P_{TLU}.$$

We favor the seasonal contract payout – 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. The rapid response capacity of seasonal insurance contracts is one of the great appeals of this approach to drought risk management as compared to reliance on food aid shipments, which typically involve lags of five months or more after the emergence of a disaster (Chantarat et al. 2007).

4.2 Variable construction and estimation of the predictive models

In order to specify the contract, we need to estimate the $X(\cdot)$ and $M(\cdot)$ functions. In estimating $X(\cdot)$ we first must control for differences in geography (e.g., elevation, hydrology, soil types) across our locations. We therefore use standardized NDVI, $zndvi$:

$$\text{(9)} \qquad zndvi_{idt} = \frac{ndvi_{idt} - E_d\left(ndvi_{idt}\right)}{\sigma_d\left(ndvi_{idt}\right)}$$

where $ndvi_{idt}$ is the NDVI for pixel i for dekad d of year t, $E_d\left(ndvi_{idt}\right)$ is the long-term mean of NDVI values for dekad d of pixel i taken over 1982-2008 and $\sigma_d\left(ndvi_{idt}\right)$ is the long-term standard deviation of NDVI values for dekad d of pixel i taken over 1982-2008. Positive (negative) $zndvi_{idt}$ represents relatively better (worse) vegetation conditions relative to the long-term mean. Figure 4 depicts the NDVI and $zndvi$ series for the Marsabit locations.

We are now in the position to estimate the predictive relationship $M(\cdot)$ that maps area-average seasonal livestock mortality onto *zndvi*. But 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 of only result from the preceding season – that still allows us to control for path-dependence. We estimate a regime-switching regression model with multiple regressors based on different functions of cumulative *zndv*i beginning during the paired season before the contract period begins. We now explain each of these variables in turn.

The cumulative variables we use are constructed as follows. All are depicted in Figure 5, which matches the seasonal IBLI contract structure with these cumulative vegetation index regressors. The first we discuss is the regime switching variable, which allows for there to exist different relationships between $zndvi_{idt}$ and area average livestock mortality depending on whether it is a good or bad season. Because we want this variable to be unobserved by all parties when the contract is struck, we use the year-long cumulative dekadal $zndvi$ from the beginning of the last rainy season until the end of the contract season. Thus, for the LRLD (SRSD) contract season, $Czndvi\_pos_{st}$ runs from the first dekad of October (March), until the end of the contract period season, i.e., the last dekad of September (February):

$$Czndvi\_pos_s = \sum_{d \in T^s_{pos}} zndvi_{ds} \tag{10}$$

where T^s_{pos} = October – September (March – February) if s = LRLD (SRSD). When $Czndvi\_pos_{st}$ is negative, this implies a worse than normal year, so we loosely term the regime $Czndvi\_pos_{st} < 0$ a "bad climate year," although this could be due to stocking rate or other drivers, not just precipitation. We observe that all past major droughts fell into this regime.

Thus, we estimate the relationship in (3) for each cluster as:

$$M_{1ls} = M_1\left(X(ndvi_{1ls})\right) + \varepsilon_{1ls} \qquad \text{if } Czndvi\_pos_{ls} \geq \gamma \quad \text{(good climate regime)}$$
$$M_{2ls} = M_2\left(X(ndvi_{2ls})\right) + \varepsilon_{2ls} \qquad \text{if } Czndvi\_pos_{ls} < \gamma \quad \text{(bad climate regime)} \tag{11}$$

where $Czndvi\_pos_{ls}$ determines the climate regime into which each season belong: a good-climate regime ($Czndvi\_pos_{ls} > 0$) or a bad one ($Czndvi\_pos_{ls} < 0$). γ is the critical threshold to be determined endogenously.[7] Appendix Table 1 displays descriptive statistics of the regressors and mortality data by regime.

The second cumulative vegetation index variable captures the state of the rangeland at the commencement of the contract period. This variable, $Czndvi\_pre_s$, captures cumulative *zndvi* from the start of the preceding rainy season until the start of the contract season, i.e., for LRLD (SRSD) contracts based on cumulative *zndvi* from the first dekad of October (March) – the start of the preceding short (long) rains – until the first dekad of March (October), as follows:

$$Czndvi\_pre_s = \sum_{d \in T^s_{pre}} zndvi_{ds} \tag{12}$$

where T^s_{pre} = October – March (March – October) if s = LRLD (SRSD). 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 intertemporal adverse selection. Because most of the observations are known ex ante to both parties, however, that effect should be minimal.

The third and fourth variables build on the concept of cooling or heating degree days used in weather derivatives contracts. These capture the accumulation of negative (positive) *zndvi* over the period of the current season, e.g., March-September (October-February) for LRLD (SRSD) season, respectively. The negative cumulative measures variable is

$$CNzndvi_s = \sum_{d \in T^s} \left| Min(zndvi_{ds}, 0) \right| \tag{13}$$

while the positive cumulative effects analog variable is

$$CPzndvi_s = \sum_{d \in T^s} Max(zndvi_{ds}, 0) \tag{14}$$

where T^s = March – September (October – February) if s = LRLD (SRSD). These capture the cumulative intensity of adverse (favorable) dekads within the contract period.

[7] We verified the intuition that γ=0 by solving for the threshold value γ that maximizes goodness of fit in estimating equation (11) and confirmed that it is indeed γ=0.

Catastrophic drought seasons routinely exhibit a continuous downward trend in cumulative $zndvi$, leading to a large value for *CNzndvi*, which should have a significantly positive impact on mortality. Similarly, *CPzndvi* 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 contract is struck, there is no information asymmetry with respect to these variables. Based on the $Czndvi$ path, it thus captures not only the adverse climate impact resulted from the preceding and current rain season, but also the intensity of adverse climate.

These cumulative vegetation indices effectively capture the myriad, complex interactions between climate and stocking rates, 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' data available for each location, limited degrees of freedom preclude estimating location-specific predictive models. Insurance companies would be unlikely to implement contracts at such high spatial resolution anyway, so this is not a serious problem. 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.

5. Estimation results and out-of-sample performance evaluation

The estimation results for equation (11) are reported in Table 3. These models explain area average mortality reasonably well, with an 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 regressor and livestock mortality. Of course, this makes intuitive sense as variation in good range conditions should not have a systematic effect on livestock survival.

In the bad climate regime, however, we see precisely the patterns anticipated. The initial state of the system, as reflected in $Czndvi\_pre$, 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 $CPzndvi$ ($CNzndvi$), the lower (higher) herd mortality rates, although those coefficient estimates are statistically significant only in Laisamis cluster, where pastoralists are less migratory and thus brief spells of favorable conditions are less likely to attract transhumant herd movements to take advantage of transiently available forage and water.

The regression coefficient estimates are themselves of limited interest, however. The real question is whether the predictions of livestock mortality prove sufficiently accurate to serve as a reasonable foundation for livestock insurance for the region. In addition to the basis risk portion of livestock mortality in the region that the model inherently cannot explain, there is also the possibility of specification 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.

The limited size of the ALRMP sample precludes setting aside some of those data for out of sample performance evaluation. But we can use 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,[8] to test out of sample forecast accuracy. Predicted area average mortality rates for these locations were then constructed based on the established cluster-specific response functions and location-specific NDVI data.

Define forecast error as the difference between actual area average mortality rate less the predicted mortality rate. A positive forecast error thus implies underprediction of the mortality rate, which would favor insurers; a negative error indicates overprediction of mortality, which could benefit insurance holders. Table 4 reports the distributions of out of sample forecast errors by cluster. In each case, 7/8 (88%) of errors were less than 10% in absolute magnitude, with one single observation off by more than 25%, an under-(over-)prediction in Dirib Gumbo (North Horr) in the 2000 SRSD season.

We also tested the performance of the IBLI contract in correctly triggering decision for insurance payouts at different strike levels. The errors of greatest concern are when the insured are paid when they should not be (type 1 error) or not paid when they should have been (type 2 error). Table 5 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 well-known severe drought events reported by communities with the predicted area average mortality constructed using their available dekadal NDVI data from 1982-2008. We find the predicted mortality index time series quite accurately capture 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.[9] This is a more statistically casual approach to forecast evaluation, but encompasses a longer time period and we find it effective for communicating to local stakeholders the potential to use statistical models to accurately capture average livestock mortality experience for the purposes of writing IBLI contracts.

[8] Kargi and Dirib Gombo are also not the locations we studied in the forecasting model, though their common characteristics fit them in their respective cluster.

[9] Figures depicting the time series of predicted mortality, by location, are available from the authors by request, so as related statistics of other locations considered in this paper.

6. IBLI pricing and risk exposure analysis

The predicted mortality profiles just describe are a key input for determining the distribution of predicted area average herd mortality rates – a vegetation-based livestock index for IBLI – and thus the actuarially fair price of IBLI based on historical data. Summary statistics of the main locations are shown in Table 6. On average, predicted mortality is lower in Laisamis than in Chalbi, with higher predicted mortality and larger variability during the SRSD (LRLD) season in Chalbi (Laisamis) cluster and higher probability of indemnity payout for any strike level in Chalbi than in Laisamis.

We can now price IBLI. There are two comparable approaches to pricing an insurance contract, based on different underlying distributions. The first is a simple historical burn rate approach, in which the contract is priced based purely on the available historical distribution of vegetation data. The second is the simulation approach, which involves first estimation parametrically or semi-parametrically the distributions of the underlying vegetation index ($zndvi$) and then pricing the contracts based on those estimated distributions. The second approach has the advantage of assigning non-zero probabilities to events that may not appear in the available historical data, but the disadvantage of assigning probabilities based on estimating probabilities without knowing the true data generating process.

In this paper, we report the historical burn rate pricing based on 27 years of available NDVI data because (i) those data seem adequate to capture most of the relevant risk experience in the system, (ii) the insurance companies in the region primarily use the burn rate approach to pricing, and (iii) our preliminary attempts at estimating the underlying density function generate the observed NDVI data – which exhibit seemingly complex autoregressive and nonstationary properties – were unconvincing to us; so we leave parametric pricing of IBLI contracts for future research.

6.1 Unconditional pricing

We consider first a seasonal contract that makes indemnity payouts in either season (SRSD or LRLD). The actuarially fair premium rate per season quoted as percentage of insured herd value for location l in season s covering the difference between the (predicted area average herd mortality) index, $\hat{M}_{ls}$, and the contractual strike level M_l^* can be written as:

$$(15) \qquad p_{ls}\left(\hat{M}_{ls} \mid M_l^*\right) = \frac{1}{S}\sum_{s=1}^{S} Max\left(\hat{M}_{ls}(zndvi_{ls}) - M_l^*, 0\right)$$

where we average results over S = 54 seasons of available NDVI data. If one assumes that a proportional premium load $\alpha > 0$ is applied to the actuarially fair premium to cover other risk and transaction costs, then the loaded premium simply becomes $(1+\alpha)\, p_{ls}\left(\hat{M}_{ls} \mid M_l^*\right)$.

Table 7 reports the fair insurance premium rates (%), their standard deviations and US dollar equivalent premia per TLU insured[10] for seasonal contracts with various strikes for locations. Because episodes of high die-offs are more frequent in Chalbi than in Laisamis (Table 6), fair premium rates are likewise higher there. But the rates are reasonable, only 2-5% of the insured livestock value for the coverage beyond 10% mortality per season and 1-2% of the insured livestock value for coverage beyond 20% mortality per season.

We next consider a one-year contract comprised of two seasonal contracts (and thus two possible payouts per year). The actuarially fair premium rate (%) is:

$$(16) \qquad p_{lt}\left(\hat{M}_{ls} \mid M_l^*\right) = \frac{1}{T}\sum_{t=1}^{T}\sum_{s\in t} Max\left(\hat{M}_{ls}(zndvi_{ls}) - M_l^*, 0\right),$$

where T covers the available 27 years of data. The fair premium rates (%), standard deviations and US dollar equivalent premia per TLU are reported in the top panel of Table 8. Intuitively, the annual premium is roughly twice as much as the seasonal premium. Fair annual premium rates decline as the strike mortality increases, e.g., from 5-9% at a strike of 15%, to 3-5% for strike mortality of 20%, to just 1-3% at a strike of 20%. By having pastoralists retain the layer of small risks, index insurance appears affordable even in the face of recurring severe droughts. 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. 2009b and 2009c).

6.2 Conditional pricing

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 accordingly. The simplest way is to price the contract conditional on the observed cumulative $zndvi$ from the beginning of 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 regime threshold $Czndvi\_beg_{ls} = 0$ analogous to that found in our earlier estimation, the two conditional annual premia based are simply:

$$(17) \quad p_{lt}\left(\hat{M}_{ls} \mid M_l^*, Czndvi\_beg_{ls} \geq 0\right) = E\left(\sum_{s\in t} Max\left(\hat{M}_{ls} - M_l^*, 0\right) \mid Czndvi\_beg_{ls} \geq 0\right)$$

[10] The dollar premium values are computed according to $p_{ls}\left(\hat{M}_{ls} \mid M_l^*\right) \cdot P_{TLU}$ at November 2008 exchange rates (79.2KSh/US$) assuming an average value per TLU of KSh12,000, which is approximately US$150, per data we collected in these locations in summer 2008.

$$p_{lt}\left(\hat{M}_{ls} \mid M_l^*, Czndvi\_beg_{ls} < 0\right) = E\left(\sum_{s\in t} Max\left(\hat{M}_{ls} - M_l^*, 0\right) \mid Czndvi\_beg_{ls} < 0\right).$$

As Table 8 shows, the two conditional premia vary markedly. When the ex ante rangeland state is favorable, premia are only 2-5% for contracts with a 10% strike. But when the state of nature is bad, those rates jump to 9-11%. 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 issues.

6.3 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., in 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[11] in Marsabit district for a total liability of $75,000/location. A standard insurance loss ratio (L_t) for a portfolio in year *t* that consists of *L* locations' coverage is

$$(18) \qquad L_t = \frac{\sum_{l\in L} \Pi_{lt}}{\sum_{l\in L} \mathrm{P}_{lt}} \quad ,$$

where Π_{lt} represents the total indemnity payments in year *t* for the total liability in location *l* and P_{lt} is the total pure premium collected. The loss ratio thus provides a good estimate of the covariate risk that remains after pooling risk across locations. When $L_t > 1$ the pure premiums would not have covered total indemnity payments that year.

Appendix Table 2 reports yearly loss ratios for various strike levels and under conditional and unconditional pricing. Over the full period, loss ratio exceeds one roughly one year in three, and sometimes for several years in a row (e.g., 2004-7 in Chalbi contracts) or by a very large margin (e.g., 2.5-6.4 in 2005). Pooling risk between the two clusters reduces variation in the loss ratio and thus underwriter risk exposure.

[11] These ten locations are the seven used for index construction plus three others in which we have gathered household and NDVI data; Kargi in Chalbi cluster and Dirib Gumbo in Laisamis cluster with PARIMA (also used in out-of-sample tests) and Balesa in Chalbi cluster with ALRMP's phase II data available from January 2005. Value per TLU in each location is again assumed at $150.

Table 9 reports the probability distribution of the yearly loss ratios associated with underwriting contracts with different strikes and (conditional or unconditional) pricing for the full set of ten locations. The loss ratio over a τ - year time period of the insurance portfolio that covers L locations is calculated as[12]

$$(19) \qquad L_\tau = \frac{\sum_{t\in\tau}\sum_{l\in L}\Pi_{lt}}{\sum_{t\in\tau}\sum_{l\in L}\mathrm{P}_{lt}} \; .$$

As Table 9 indicates, for the most exposed case of 10% strike contracts with unconditional premium pricing, the single year risk of a loss ratio greater than 2 is 26%, but this falls to just 8% with two year pooling and to zero when risk is pooled over a five-year period. Of course, the reduced loss exposure risk necessarily comes at the cost of lower probability of large profits from the contract. Figure 6 presents a sample cumulative distribution of the loss ratios reported in Table 9, clearly showing how a state-conditional pricing and longer-term commitment each reduce extreme outcomes sharply. Of course, with premium loadings, underwriter risk exposure would further 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% (32%) for a 10% strike contract to 68% (49%) for a 30% strike contract (Table 10). Appendix Table 3 shows the detail. These high estimated pure reinsurance rates only take into consideration the local drought risk profile, however, and should fall markedly as international reinsurers are better able to diversify these risks in international financial markets. Indeed, this diversification opportunity through international risk transfer is one of the key benefits of developing IBLI products.

7. Conclusions and some implementation challenges

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, where insurance markets are effectively absent and uninsured risk exposure is a main cause of the existence of poverty traps. It has gone on to explain the design of an IBLI product to insure against livestock mortality in order to protect the main asset households in this region hold. We parameterize the index using longitudinal observations of household-level herd mortality, fit to high quality, objectively verifiable remotely sensed vegetation data not manipulable by either party to the contract and available at low cost and in near-real time. The resulting index performs very well out of sample, both when tested against other

[12] We abstract away from the need to discount the financial variables over time.

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. Finally, we established that IBLI should be readily reinsurable on international markets.

The development of the IBLI contract is promising because of the opportunity it opens up to bring insurance to many places where uninsured risk remains a main driver of poverty. Extended time series of remotely sensed data are available worldwide at high quality and low cost. Wherever there also exist longitudinal 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 any systematic patterns so that prospective insurance purchasers can be fully informed as to how well suited (or not) the index-based contract might be for their individual case. Chantarat et al. (2009b) explores this issue 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 (Gine et al., 2007; 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 experiments with using simulation games in the field with prospective insurance purchasers shows significant promise as a means of both explaining how index insurance products work and generating demand for the product (Lybbert et al. 2009).

Third, the infrastructure deficiencies that lead to high transactions costs in verifying individual claims in remote rural areas still feed high costs of product marketing and claims settlement. Development of cost-effective agent networks for reliable, low-cost product marketing and service is a challenge. In the northern Kenya IBLI case, our commercial partners are tapping into a network of local agents equipped with electronic, 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 payments 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 of Kenyan insurance companies that have ventured into the agricultural sector, using the less risky areas to 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.

These implementation challenges notwithstanding, IBLI shows considerable promise as effective drought risk management strategies and widely acknowledged as essential components to effective poverty alleviation in the pastoral areas of east Africa. By addressing serious problems of covariate 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 location rainfall station) 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 in the coming months, 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.

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Table 1: Descriptive Statistics, by Cluster

Cluster	Location	Annual rain (mm)		Long rain (mm)		Short rain (mm)		NDVI		Livestock Allocation (headcount)		
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	% Camel	% Cattle	%Smallstock
Chalbi	North Horr	237	105	131	72	75	73	0.11	0.03	0.10	0.03	0.86
	Kalacha	236	105	132	85	80	72	0.12	0.03	0.14	0.00	0.85
	Maikona	235	96	125	62	87	63	0.11	0.04	0.11	0.02	0.87
Laisamis	Karare	367	159	206	106	133	81	0.34	0.11	0.00	0.74	0.26
	Logologo	326	138	178	94	123	72	0.24	0.12	0.05	0.31	0.64
	Ngurunit	255	135	147	88	88	75	0.26	0.08	0.07	0.19	0.74
	Korr	255	125	146	92	89	63	0.17	0.07	0.05	0.03	0.92

Table 2: Seasonal Herd Mortality Rates, 2000-2008

Cluster/ Location	No. of Obs.	Overall				LRLD Season		SRSD Season		Proportion of 16 Seasons with					
		Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	M>10%	M>15%	M>20%	M>25%	M>30%	M>50%
Chalbi	48	10%	16%	0%	67%	7%	8%	13%	20%	0.33	0.26	0.15	0.15	0.09	0.06
North Horr	16	9%	15%	1%	59%	6%	9%	11%	20%	0.25	0.19	0.13	0.13	0.06	0.06
Kalacha	16	13%	22%	0%	67%	7%	10%	18%	29%	0.38	0.31	0.19	0.19	0.13	0.13
Maikona	16	10%	11%	0%	39%	8%	7%	13%	15%	0.38	0.31	0.13	0.13	0.06	0.00
Laisamis	64	10%	13%	0%	57%	13%	15%	8%	11%	0.33	0.22	0.19	0.19	0.14	0.02
Karare	16	15%	16%	0%	57%	17%	19%	12%	12%	0.44	0.25	0.25	0.25	0.19	0.06
Logologo	16	8%	14%	0%	42%	10%	16%	6%	12%	0.19	0.19	0.19	0.19	0.13	0.00
Ngurunit	16	8%	11%	0%	36%	11%	14%	5%	8%	0.31	0.25	0.13	0.13	0.06	0.00
Korr	16	11%	13%	1%	41%	13%	12%	9%	14%	0.38	0.19	0.19	0.19	0.19	0.00

Table 3: Regime Switching Model Estimates of Area Average Livestock Mortality

Chalbi Model		
Number of observations		48
R-squared		0.5689
Adj R-squared		0.5187
Good-climate regime (Czndvi_pos>=0)		
Mortality	Coeff.	Std.Err
Czndvi_pos	0.0024	0.0018
Bad-climate regime (Czndvi_pos<0)		
Mortality	Coeff.	Std.Err
Czndvi_pre	-0.0187***	0.0051
CNzndvi	0.0018	0.0033
CPzndvi	-0.0064	0.0087
SRSD	0.0354	0.0564

Laisamis Model		
Number of observations		64
R-squared		0.6554
Adj R-squared		0.6062
Good-climate regime (Czndvi_pos>=0)		
Mortality	Coeff.	Std.Err
Czndvi_pre	-0.0003	0.0028
CNzndvi	0.0087	0.0081
CPzndvi	0.0013	0.0024
SRSD	0.0147	0.0402
Bad-climate regime (Czndvi_pos<0)		
Mortality	Coeff.	Std.Err
Czndvi_pre	-0.0093***	0.0024
CNzndvi	0.0117***	0.0022
CPzndvi	-0.0111**	0.0049
SRSD	-0.0446*	0.0299

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

Table 4: Out of Sample Forecast Performance

Error Magnitude (absolute value)	Proportion of Sample	
	Chalbi Model	Laisamis Model
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

* Out of sample errors are based on 2000-2002 PARIMA data for North Horr and Kargi in Chalbi cluster and Logologo and Dirib Gombo for Laisamis cluster.

Table 5: Testing Indemnity Payment Errors

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

* Out-of-sample errors are based on 2000-2002 PARIMA data for North Horr and Kargi in Chalbi cluster and Logologo and Dirib Gombo for Laisamis cluster.

Table 6: Predicted Seasonal Mortality Rates, 1982-2008

Cluster/ Location	No. of Obs.	Overall				LRLD Season		SRSD Season		Proportion of 16 Seasons with				
		Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	M>10%	M>15%	M>20%	M>25%	M>30%
Chalbi	162	10%	10%	0%	37%	8%	8%	13%	11%	0.40	0.30	0.20	0.10	0.04
North Horr	54	9%	11%	0%	37%	7%	8%	12%	13%	0.34	0.28	0.21	0.11	0.06
Kalacha	54	11%	10%	0%	36%	8%	9%	14%	11%	0.45	0.32	0.21	0.13	0.06
Maikona	54	10%	9%	0%	31%	7%	7%	12%	10%	0.42	0.30	0.19	0.06	0.02
Laisamis	216	8%	9%	0%	34%	10%	9%	7%	7%	0.29	0.21	0.12	0.06	0.02
Karare	54	8%	8%	0%	34%	9%	9%	6%	6%	0.28	0.15	0.09	0.04	0.02
Logologo	54	9%	8%	0%	30%	11%	10%	8%	7%	0.34	0.28	0.15	0.06	0.02
Ngurunit	54	8%	9%	0%	34%	10%	9%	6%	7%	0.23	0.17	0.11	0.08	0.04
Korr	54	9%	9%	0%	31%	11%	10%	6%	7%	0.32	0.25	0.13	0.06	0.02

Table 7: Unconditional Fair Seasonal Premium Rates at Various Strike Levels

Cluster/ Location	% Premium Rate (*p*)										US$ Premium/TLU				
	M* = 10%		M* = 15%		M* = 20%		M* = 25%		M* = 30%		At Strike (M*)				
	p	S.D.(*p*)	*p*	S.D.(*p*)	*p*	S.D.(*p*)	*p*	S.D.(*p*)	*p*	S.D.(*p*)	10%	15%	20%	25%	30%
Chalbi															
North Horr	4.3%	7.5%	2.8%	5.5%	1.5%	3.8%	0.7%	2.3%	0.3%	1.2%	$6.5	$4.2	$2.3	$1.0	$0.4
Kalacha	4.9%	7.2%	2.9%	5.4%	1.5%	3.6%	0.6%	2.0%	0.2%	0.9%	$7.4	$4.4	$2.3	$0.9	$0.3
Maikona	3.7%	5.9%	2.0%	4.1%	0.9%	2.4%	0.3%	1.1%	0.0%	0.2%	$5.6	$3.0	$1.3	$0.4	$0.0
Laisamis															
Karare	2.2%	4.9%	1.1%	3.3%	0.5%	2.1%	0.2%	1.3%	0.1%	0.6%	$3.3	$1.7	$0.7	$0.3	$0.1
Logologo	3.4%	5.6%	1.8%	3.7%	0.7%	2.0%	0.1%	0.7%	0.0%	0.0%	$5.0	$2.7	$1.1	$0.2	$0.0
Ngurunit	2.6%	6.0%	1.6%	4.4%	0.9%	2.9%	0.4%	1.7%	0.1%	0.7%	$3.9	$2.4	$1.3	$0.6	$0.2
Korr	3.1%	5.7%	1.7%	3.8%	0.7%	2.2%	0.2%	1.0%	0.0%	0.2%	$4.7	$2.6	$1.1	$0.3	$0.0

Table 8: Unconditional Vs. Conditional Fair Annual Premium Rates

Location	% Premium Rate (*p*)										US$ Premium/TLU				
	M* = 10%		M* = 15%		M* = 20%		M* = 25%		M* = 30%		At Strike (M*)				
	p	S.D.(*p*)	*p*	S.D.(*p*)	*p*	S.D.(*p*)	*p*	S.D.(*p*)	*p*	S.D.(*p*)	10%	15%	20%	25%	30%
Unconditional															
North Horr	8.8%	11.7%	5.7%	8.2%	3.2%	5.2%	1.4%	3.2%	0.5%	1.6%	$13.2	$8.6	$4.7	$2.1	$0.8
Kalacha	9.8%	11.2%	5.8%	8.0%	3.1%	5.0%	1.3%	2.8%	0.4%	1.3%	$14.7	$8.6	$4.6	$1.9	$0.5
Maikona	7.5%	8.9%	4.1%	5.8%	1.8%	3.3%	0.5%	1.6%	0.1%	0.3%	$11.3	$6.1	$2.7	$0.8	$0.1
Karare	4.2%	7.3%	2.2%	4.6%	0.9%	2.9%	0.4%	1.8%	0.2%	0.8%	$6.4	$3.3	$1.4	$0.5	$0.2
Logologo	6.5%	8.6%	3.5%	5.5%	1.4%	2.8%	0.3%	1.0%	0.0%	0.0%	$9.8	$5.3	$2.1	$0.4	$0.0
Ngurunit	5.2%	10.1%	3.2%	7.5%	1.7%	5.2%	0.8%	3.1%	0.3%	1.2%	$7.8	$4.9	$2.6	$1.3	$0.4
Korr	6.1%	9.2%	3.4%	6.2%	1.4%	3.8%	0.4%	1.6%	0.1%	0.3%	$9.2	$5.1	$2.1	$0.7	$0.1
Conditional on observed Czndvi_beg>=0 before the sale period															
North Horr	4.7%	8.4%	3.3%	6.4%	2.0%	4.5%	1.0%	2.9%	0.4%	1.5%	$7.1	$4.9	$3.0	$1.5	$0.6
Kalacha	5.5%	7.6%	3.1%	5.6%	1.7%	3.7%	0.7%	1.9%	0.1%	0.6%	$8.3	$4.7	$2.5	$1.1	$0.2
Maikona	5.0%	7.1%	2.9%	4.9%	1.3%	3.2%	0.5%	1.6%	0.1%	0.3%	$7.5	$4.3	$1.9	$0.7	$0.1
Karare	1.2%	4.1%	0.6%	1.9%	0.2%	0.5%	0.0%	0.0%	0.0%	0.0%	$1.8	$0.9	$0.2	$0.0	$0.0
Logologo	1.9%	4.0%	0.7%	1.6%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	$2.8	$1.0	$0.0	$0.0	$0.0
Ngurunit	0.7%	2.3%	0.2%	1.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	$1.1	$0.3	$0.0	$0.0	$0.0
Korr	1.4%	3.4%	0.3%	1.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	$2.2	$0.5	$0.0	$0.0	$0.0
Conditional on observed Czndvi_beg<0 before the sale period															
North Horr	12.0%	13.0%	7.6%	9.0%	4.1%	5.7%	1.7%	3.4%	0.6%	1.7%	$18.0	$11.4	$6.1	$2.6	$0.9
Kalacha	12.5%	12.4%	7.4%	8.9%	4.0%	5.5%	1.6%	3.2%	0.5%	1.6%	$18.7	$11.1	$6.0	$2.4	$0.7
Maikona	9.0%	9.6%	4.8%	6.2%	2.1%	3.4%	0.6%	1.6%	0.0%	0.2%	$13.5	$7.2	$3.1	$0.8	$0.1
Karare	6.8%	8.5%	3.6%	5.7%	1.6%	3.8%	0.7%	2.4%	0.3%	1.1%	$10.2	$5.5	$2.4	$1.0	$0.4
Logologo	9.9%	9.5%	5.6%	6.3%	2.4%	3.4%	0.5%	1.3%	0.0%	0.0%	$14.9	$8.4	$3.7	$0.7	$0.0
Ngurunit	9.3%	12.6%	6.0%	9.6%	3.3%	6.9%	1.6%	4.1%	0.5%	1.6%	$13.9	$9.0	$5.0	$2.4	$0.8
Korr	9.3%	10.6%	5.5%	7.4%	2.3%	4.7%	0.7%	2.1%	0.1%	0.4%	$13.9	$8.2	$3.5	$1.1	$0.1

Table 9: Distribution of Estimated Loss Ratios

Probability of Loss Ratio	Unconditional Premium									Conditional Premium								
	Strike = 10%			Strike = 20%			Strike = 25%			Strike = 10%			Strike = 20%			Strike = 25%		
	Years of risk pooling			Years of risk pooling			Years of risk pooling			Years of risk pooling			Years of risk pooling			Years of risk pooling		
	1	2	5	1	2	5	1	2	5	1	2	5	1	2	5	1	2	5
Less than 0.5	0.52	0.38	0.13	0.59	0.42	0.30	0.63	0.38	0.26	0.44	0.31	0.13	0.63	0.42	0.13	0.63	0.46	0.26
Between 0.5 to 1	0.15	0.12	0.48	0.07	0.12	0.39	0.00	0.31	0.57	0.22	0.27	0.52	0.00	0.19	0.52	0.07	0.19	0.57
Between 1 to 2*	0.07	0.42	0.39	0.11	0.36	0.17	0.22	0.19	0.04	0.16	0.35	0.36	0.15	0.31	0.45	0.11	0.14	0.04
Between 2 to 3	0.19	0.07	0.00	0.11	0.04	0.13	0.00	0.00	0.13	0.19	0.08	0.00	0.19	0.07	0.00	0.11	0.08	0.13
Greater than 3	0.07	0.04	0.00	0.11	0.08	0.00	0.16	0.12	0.00	0.00	0.00	0.00	0.04	0.04	0.00	0.07	0.08	0.00

* The shaded zone represents the scenerio when underwriter experiences loss (loss ratio less than 1).

Table 10: 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%

Figure 1: Clustered Sites in Marsabit, Northern Kenya

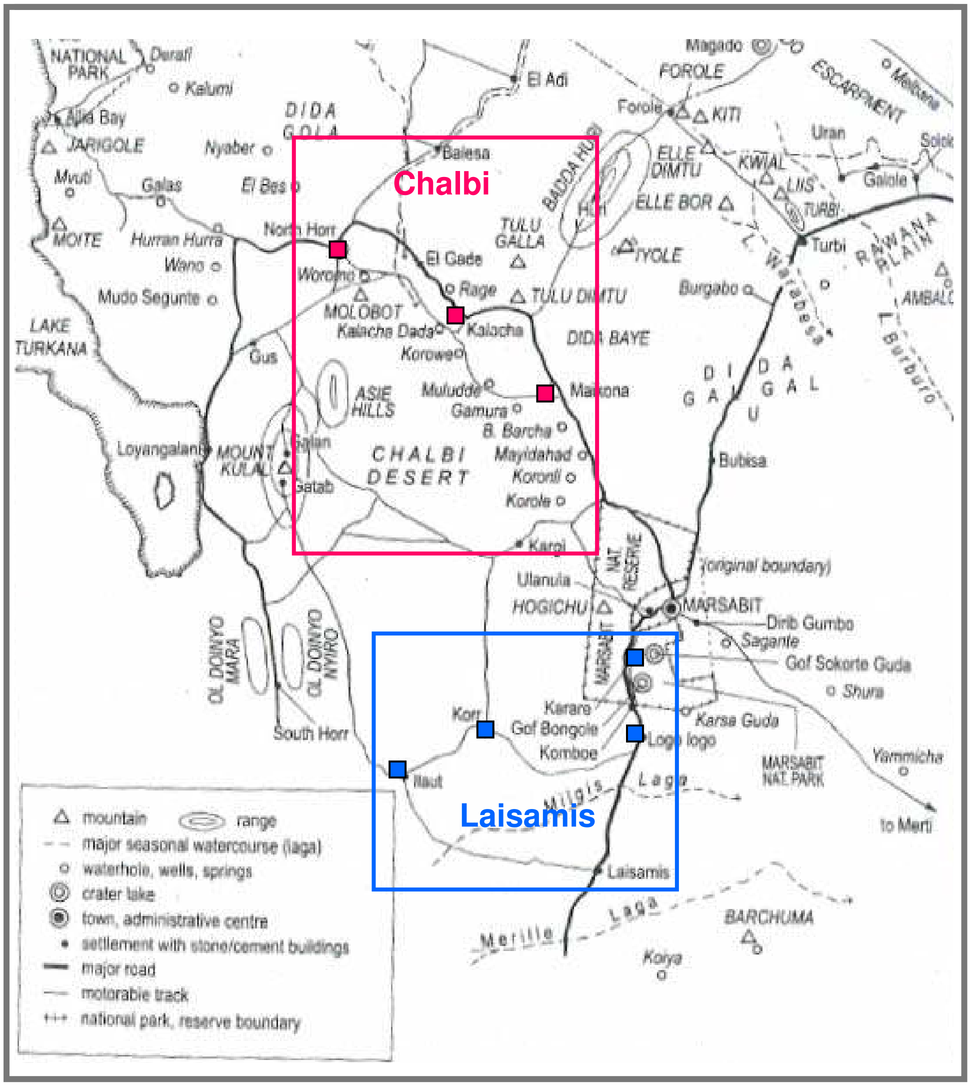


Figure 2: Seasonal TLU Mortality Rate by Clusters

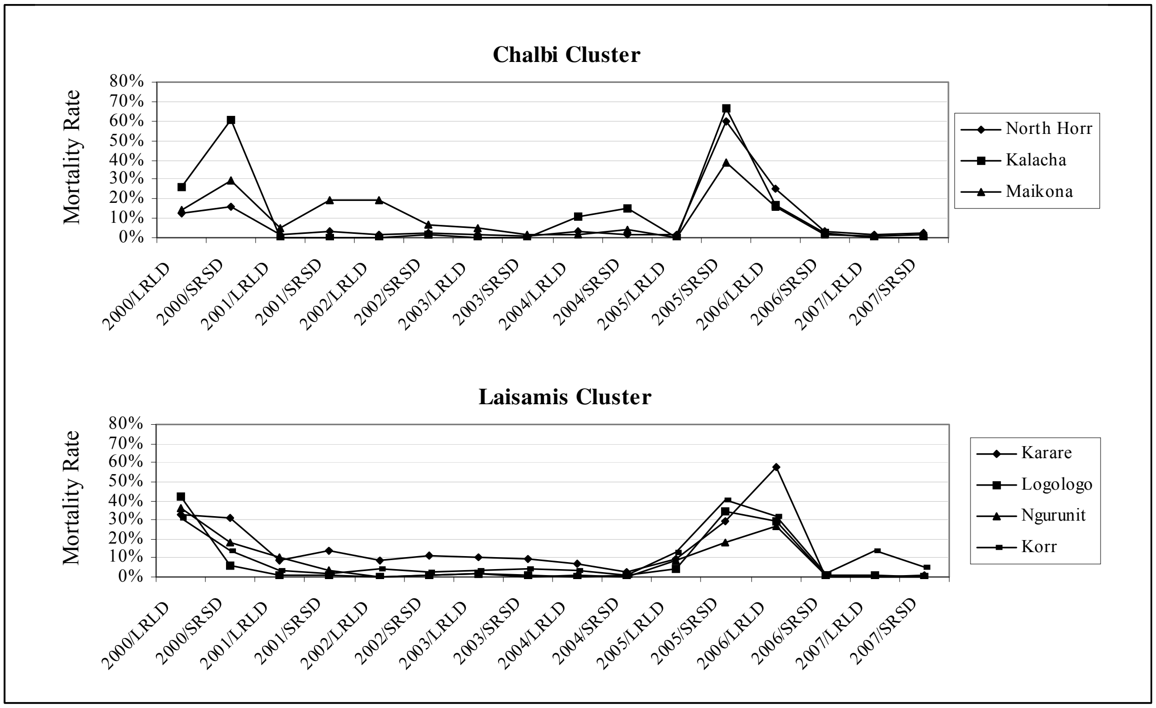


Figure 3: Temporal Structure of IBLI Contract

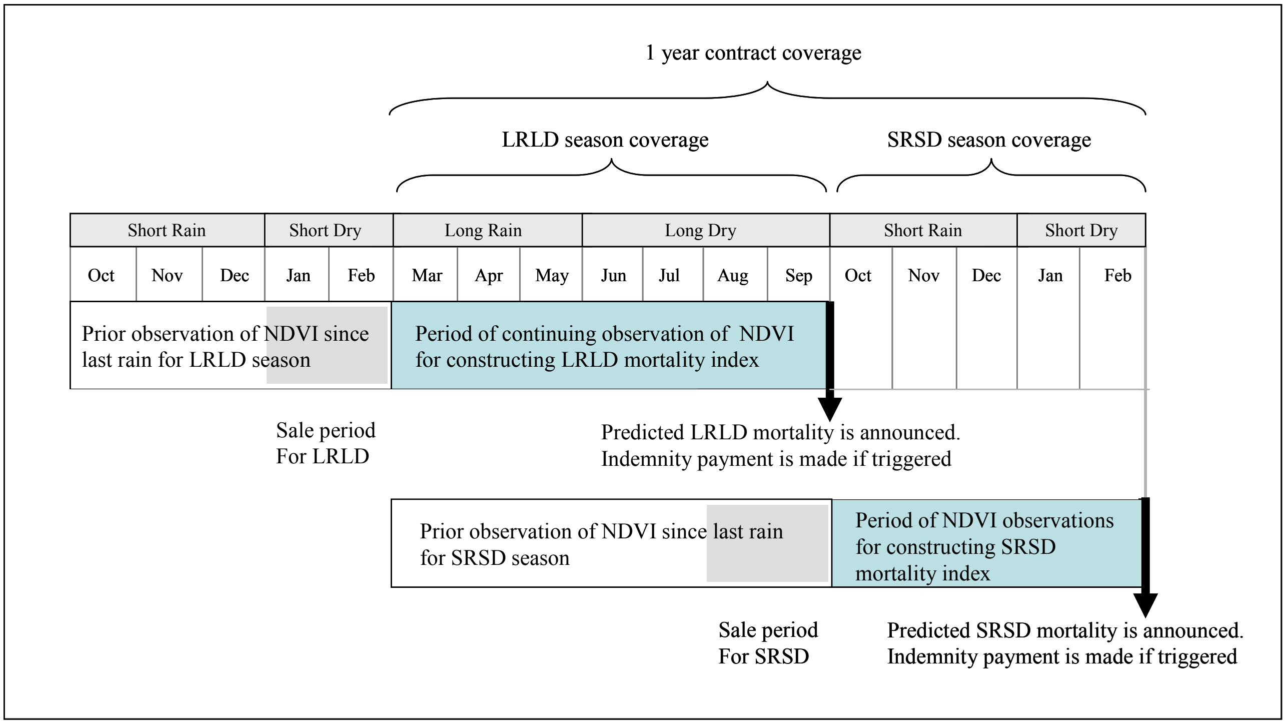


Figure 4: NDVI and *zndvi* for Locations in Marsabit, by Clusters

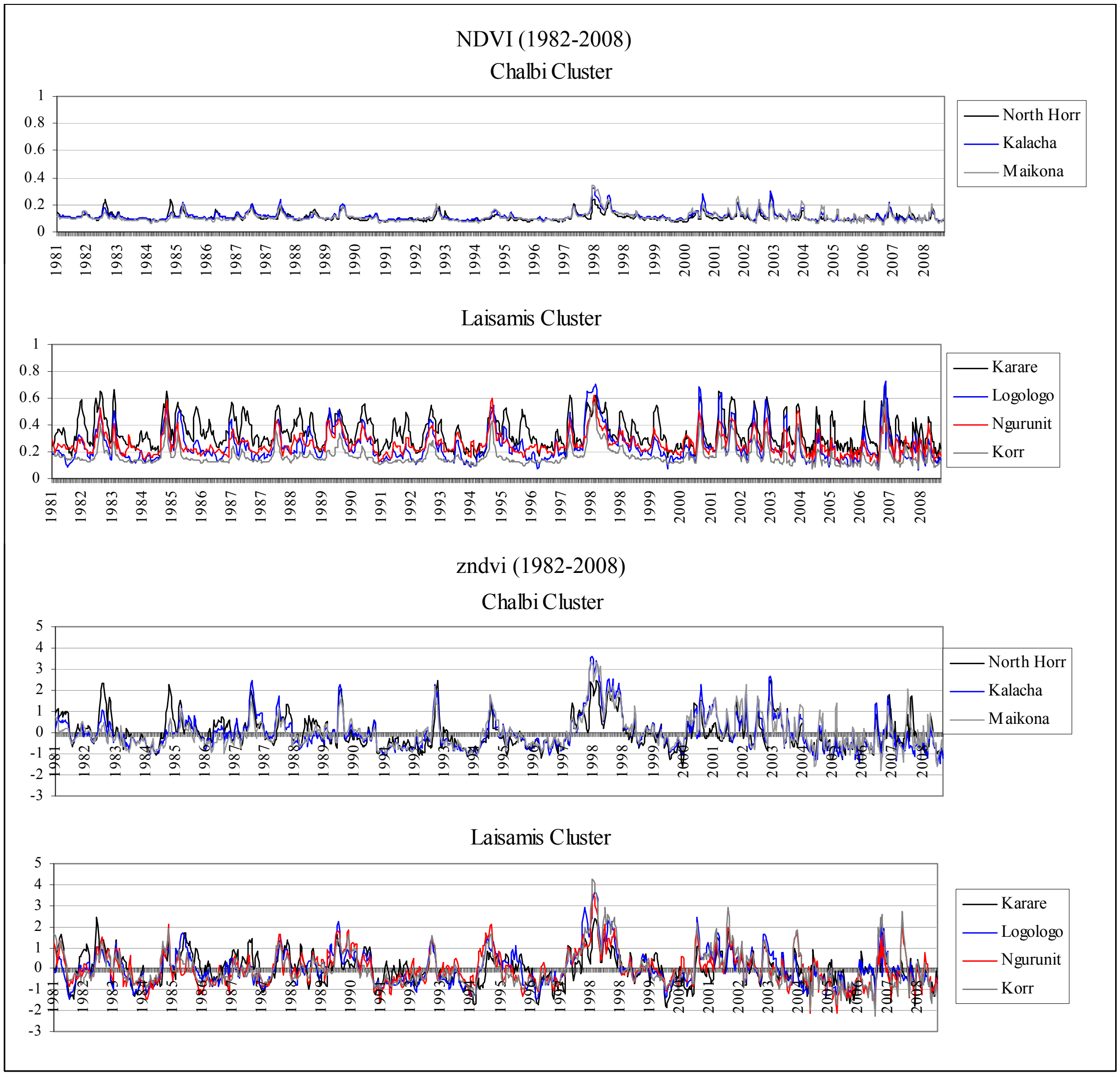


Figure 5: Temporal Structure of IBLI Contract and Vegetation Regressors

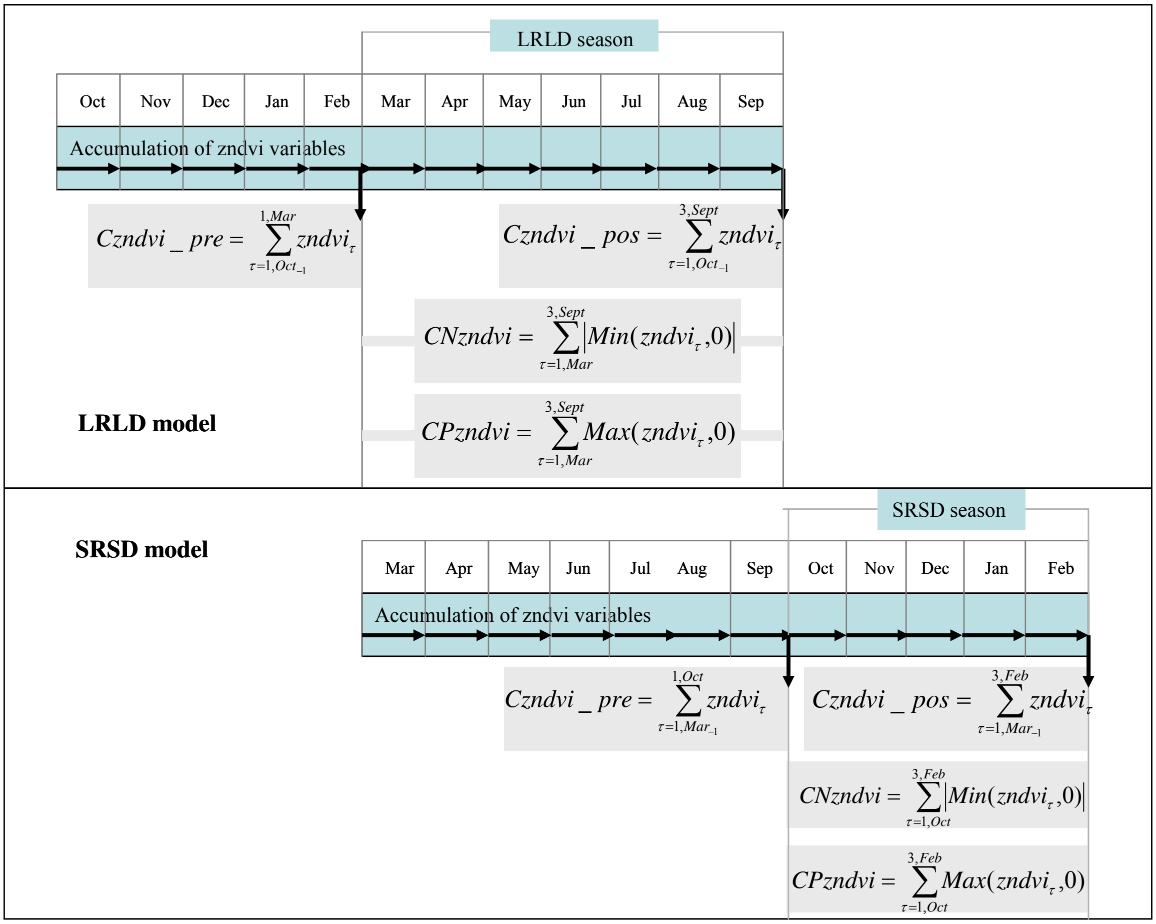
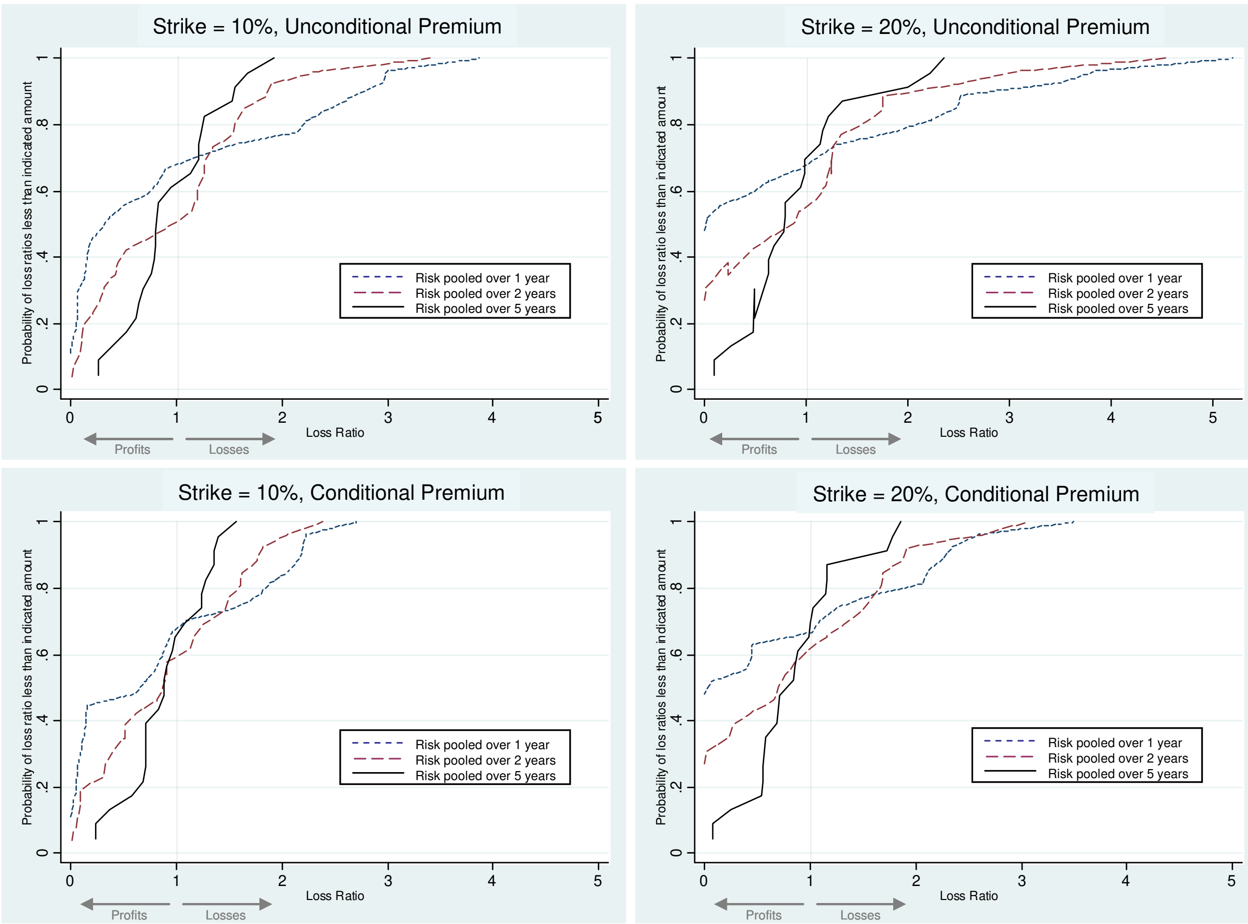


Figure 6: Loss Ratio Cumulative Distributions, by Pricing, Strike and Number of Years Risk Pooled



Appendix Table 1: 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 (Pooled)	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	
	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	
	CNzndvi	6.4	4.6	0.1	18.6	5.2	3.0	7.6	5.6	2.5	1.6	8.9	4.1	
	CPzndvi	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	
	CNzndvi	6.9	5.0	1.6	18.6	5.4	2.9	8.4	6.4	3.3	1.3	9.7	5.1	
	CPzndvi	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	
	CNzndvi	6.6	5.0	0.6	16.3	5.3	3.7	7.9	5.9	2.1	1.5	9.4	4.2	
	CPzndvi	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	
	CNzndvi	5.6	4.0	0.1	11.1	4.8	2.7	6.4	5.0	1.9	2.0	7.8	3.1	
	CPzndvi	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 (Pooled)	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	
	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	
	CNzndvi	6.7	5.1	0.0	19.6	5.8	4.1	7.7	5.9	2.5	2.1	9.6	4.6	
	CPzndvi	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	
	CNzndvi	6.5	4.4	0.3	16.3	6.0	4.4	7.0	4.7	2.4	1.2	8.9	3.8	
	CPzndvi	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	
	CNzndvi	6.2	4.9	0.2	14.6	5.4	4.0	7.0	5.9	2.3	1.4	10.1	3.9	
	CPzndvi	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	
	CNzndvi	7.0	6.0	0.2	19.6	5.7	4.8	8.3	7.1	2.5	2.5	9.7	5.8	
	CPzndvi	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	
	CNzndvi	7.2	5.5	0.0	17.2	6.0	4.2	8.4	6.6	2.9	3.4	9.8	4.9	
	CPzndvi	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 2: Estimated Annual Loss Ratios under Pure Premia, 1982-2008

Year	Unconditional Premium						Conditional Premium					
	Strike = 10%			Strike = 20%			Strike = 10%			Strike = 20%		
	Chalbi	Laisamis	All	Chalbi	Laisamis	All	Chalbi	Laisamis	All	Chalbi	Laisamis	All
1982	0.0	0.2	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0
1983	0.5	0.2	0.4	0.0	0.0	0.0	0.8	0.7	0.8	0.1	0.0	0.1
1984	2.3	3.2	2.7	2.5	5.6	3.5	1.8	2.0	1.9	1.8	3.2	2.3
1985	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1986	0.7	1.2	0.9	0.5	0.4	0.5	0.9	0.8	0.9	0.6	0.3	0.4
1987	0.2	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.2	0.0	0.0	0.0
1988	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
1989	0.3	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.1	0.0	0.0	0.0
1990	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1991	1.6	1.5	1.6	1.9	0.1	1.3	1.6	5.4	2.2	2.1	1.4	2.1
1992	2.7	1.6	2.2	2.1	1.4	1.9	2.0	1.0	1.6	1.5	0.8	1.3
1993	0.2	0.1	0.2	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0
1994	1.9	2.5	2.1	1.7	4.2	2.5	1.6	2.0	1.8	1.5	3.3	2.1
1995	0.3	0.2	0.3	0.2	0.0	0.2	0.6	0.7	0.6	0.4	0.0	0.4
1996	2.5	3.8	3.0	2.0	2.7	2.2	1.9	2.8	2.2	1.5	1.7	1.6
1997	0.2	0.0	0.1	0.0	0.0	0.0	0.2	0.0	0.1	0.0	0.0	0.0
1998	0.8	0.0	0.5	0.0	0.0	0.0	1.4	0.0	1.1	0.0	0.0	0.0
1999	0.1	0.0	0.1	0.0	0.0	0.0	0.2	0.0	0.1	0.0	0.0	0.0
2000	2.3	2.8	2.5	3.2	0.9	2.5	2.0	2.6	2.2	2.8	0.9	2.3
2001	0.0	0.2	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0
2002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2004	1.1	0.5	0.8	1.4	0.0	0.9	1.5	0.4	1.0	1.9	0.0	1.1
2005	3.3	4.8	3.9	4.6	6.4	5.2	2.5	3.0	2.7	3.4	3.6	3.5
2006	3.3	2.4	2.9	3.9	3.8	3.9	2.5	1.5	2.1	2.9	2.1	2.6
2007	1.2	0.0	0.7	1.6	0.0	1.1	0.9	0.0	0.7	1.2	0.0	1.0
2008	0.8	1.8	1.2	0.4	1.1	0.6	0.7	1.1	0.9	0.4	0.6	0.5
Mean	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	0.9	0.8	0.7	0.8
S.D.	1.1	1.4	1.2	1.4	1.9	1.4	0.9	1.3	0.9	1.1	1.1	1.0

Appendix Table 3: Annual Unconditional Premiums, Indemnities and Reinsurance for Hypothetical IBLI Contracts at 10% Strike (1982-2008)

Year	Chalbi Locations (Total liabilities = $375,000)			Laisamis Locations (Total liabilities = $375,000)			All Locations (Total liabilities = $750,000)		
	Total Pure Premium ($)	Total Indemnities ($)	100% Stop-loss Coverage ($)	Total Pure Premium ($)	Total Indemnities ($)	100% Stop-loss Coverage ($)	Total Pure Premium ($)	Total Indemnities ($)	100% Stop-loss Coverage ($)
1982	32,354	0	0	20,351	3,227	0	52,706	3,227	0
1983	32,354	15,498	0	20,351	3,800	0	52,706	19,297	0
1984	32,354	75,926	43,572	20,351	66,058	45,707	52,706	141,984	89,278
1985	32,354	0	0	20,351	0	0	52,706	0	0
1986	32,354	23,630	0	20,351	23,805	3,453	52,706	47,434	0
1987	32,354	7,543	0	20,351	859	0	52,706	8,402	0
1988	32,354	3,050	0	20,351	0	0	52,706	3,050	0
1989	32,354	9,548	0	20,351	0	0	52,706	9,548	0
1990	32,354	0	0	20,351	0	0	52,706	0	0
1991	32,354	51,333	18,979	20,351	30,481	10,129	52,706	81,814	29,108
1992	32,354	85,930	53,576	20,351	32,082	11,731	52,706	118,012	65,306
1993	32,354	5,595	0	20,351	2,326	0	52,706	7,921	0
1994	32,354	61,748	29,394	20,351	51,463	31,112	52,706	113,211	60,506
1995	32,354	10,475	0	20,351	4,060	0	52,706	14,535	0
1996	32,354	80,366	48,012	20,351	77,762	57,411	52,706	158,128	105,422
1997	32,354	6,783	0	20,351	0	0	52,706	6,783	0
1998	32,354	26,475	0	20,351	0	0	52,706	26,475	0
1999	32,354	3,516	0	20,351	0	0	52,706	3,516	0
2000	32,354	73,615	41,261	20,351	57,035	36,684	52,706	130,650	77,944
2001	32,354	0	0	20,351	3,216	0	52,706	3,216	0
2002	32,354	909	0	20,351	0	0	52,706	909	0
2003	32,354	0	0	20,351	0	0	52,706	0	0
2004	32,354	34,627	2,273	20,351	9,408	0	52,706	44,035	0
2005	32,354	105,796	73,442	20,351	97,943	77,592	52,706	203,739	151,034
2006	32,354	106,484	74,130	20,351	48,798	28,446	52,706	155,282	102,576
2007	32,354	39,098	6,744	20,351	0	0	52,706	39,098	0
2008	32,354	26,527	0	20,351	36,855	16,504	52,706	63,382	10,677
Mean	32,354	32,354	14,496	20,351	20,351	11,806	52,706	52,706	25,624
% Premium	100%	100%	45%	100%	100%	58%	100%	100%	49%

Note: Total premia ($) and indemnities ($) are calculated based on hypothetical liability of $75,000 (500 TLU×150$/TLU) per location and 5 locations in each cluster.