Index Insurance Quality and Basis Risk: Evidence from Northern Kenya

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Abstract: The number of index insurance pilots in developing countries has grown tremendously in recent years, but there has been little progress in our understanding of the quality of those products. Basis risk, or remaining uninsured risk, is a widely recognized, but rarely measured feature of index insurance product quality. This research uses eight semi-annual seasons of longitudinal household data to examine the distribution of basis risk associated with an index based livestock insurance (IBLI) product in northern Kenya. We find that IBLI coverage reduces exposure to covariate risk due to large shocks and mitigates downside risk substantially for many households, even at commercial premium rates. But index insurance is no magic bullet; insured households continue to face considerable and mostly random idiosyncratic risk. This research underscores both the promise and the need for caution when promoting index insurance as a risk mitigation tool and the importance of product quality evaluation.

Key words: index insurance; basis risk; IBLI; pastoralists

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Recent years have seen a surge in the promotion and piloting of index insurance projects for agricultural households in developing countries. Unfortunately, most pilot projects have met with extremely low demand, even when premiums have been subsidized and extension efforts have been included. Basis risk, or residual risk not covered by an index insurance product, is often cited as a likely cause of low demand (e.g., Smith and Watts 2009; Hazell and Hess 2010; Miranda and Farrin 2012) and has even been called "the most serious obstacle to the effectiveness of weather index insurance as a general agricultural risk management tool" (Miranda and Farrin 2012, p.48).

Product design and basis risk have been studied quite extensively within the agricultural finance and insurance literature in the context of index insurance (or weather derivatives) for crops in developed economies (e.g., Miranda 1991; Williams et al. 1993; Smith, Chouinard, and Baquet 1994; Mahul 1999; Turvey 2001; Vedenov and Barnett 2004; Woodard and Garcia 2008; Turvey and Mclaurin 2012). But those findings might not generalize to the developing country context, where basis risk remains remarkably under-researched. In a few cases authors use clever approaches to proxy for basis risk in studying the demand for index insurance (Giné, Townsend, and Vickery 2008; Mobarak and Rosenzweig 2012; Hill, Robles, and Cebellos 2013). Other articles use simulations, aggregate-level data, and/or experiments to examine basis risk (e.g., Breustedt, Bokusheva, and Heidelback 2008; Clarke 2011; Norton, Turvey, and Osgood 2012; Elabed et al. 2013; Dercon et al. 2014; Leblois, Quirion, and Sultan 2014). These studies can say little or nothing, however, about the relative magnitude or distribution of basis risk among households. To date, no study of index insurance products in developing countries offers household-level estimates of basis risk. This article fills that important void.

The lack of empirical attention to basis risk is especially disturbing because there is no guarantee that index insurance is risk reducing. In cases where an individual's idiosyncratic risk is high or if the index is inaccurate, index products can represent a costly, risk-increasing gamble rather than the risk-reducing insurance implied by their name and claimed by their underwriters. Discerning the magnitude and distribution of basis risk should be of utmost importance for organizations promoting index insurance products, lest they inadvertently peddle lottery tickets under an insurance label.

The Index Based Livestock Insurance (IBLI) product was developed and commercially piloted among pastoralists in the Marsabit region of northern Kenya in 2010 (Chantarat et al. 2013). The IBLI index predicts division average livestock mortality rates using an innovative response function that was generated econometrically using historical data on household herd losses specifically with the objective of minimizing basis risk. Because the IBLI index is measured in the same units as the insurable household losses, it allows for the direct estimation of the magnitude and cross-sectional heterogeneity of basis risk. If basis risk significantly limits the benefits from IBLI, one might naturally wonder whether other products, not designed using statistical methods to minimize basis risk, might suffer similar or worse shortcomings.

This article uses a four-year household panel dataset, which includes eight distinct semi-annual seasons of index values and household-level loss data, to examine the magnitude and components of basis risk that pastoralists would have faced if they had fully insured with IBLI over the entire survey period. Specifically, we compare households' reported livestock survival rate to the net of their reported survival rate, premium, and indemnity payments. Although our household-specific risk and basis risk parameter estimates prospectively suffer from small sample and endogeneity bias as we do not observe unrealized states of nature nor the true counterfactual livestock survival rates experienced by insured (uninsured) households in the absence of (with) insurance, these eight-season estimates relating endogenous livestock survival rates to index values represent a vast improvement over the current absence of estimates.[1]

Using standard approaches that are often used to study index insurance in high-income economies, we find that IBLI coverage significantly increases variance in livestock

[1] The small sample concern is related to non-representative weather events during the seasons observed in the data. Of the eight observed seasons, one was a severe drought that affected the entire region and has been widely referred to as a 1-in-60-year drought. In addition, there were less severe droughts in two other seasons. Thus drought conditions may be unintentionally overrepresented in the survey data.

survival rates by an average of 2.3% but improves skewness in survival rates by 37.6% (from -1.18 to -0.735). Focusing on downside risk, we find that IBLI reduces exposure to large shocks for 41.9%, 47.9% and 62.4% of households when premium rates are set at the commercial (loaded and unsubsidized) rate, the actuarially fair rate, and the subsidized rate actually offered to pastoralists, respectively. The variation in beneficiaries highlights the vital role that premium rates play in determining the benefits of insurance, which can be easily overlooked with simple variance analysis.

We then examine the components of basis risk and the factors that contribute to their heterogeneity. IBLI coverage reduces households' exposure to risk associated with large covariate shocks by an average of 63.2%, indicating incomplete coverage due to some design risk. A second, much larger, portion of basis risk arises due to idiosyncratic losses. Although droughts, which represent insurable covariate risk, are the largest reported cause of livestock mortality, there is considerable variation between households in livestock mortality rate experienced in every season. Regression analysis of this idiosyncratic risk finds that very little of it can be explained by household characteristics or by accounting for local fixed effects. By design IBLI can do nothing about this remaining seemingly random idiosyncratic risk and there are no clear avenues for using client-type specific indices to reduce it.

We also find that the degree of covariate risk is closely tied to how covariate losses are defined spatially and temporally. The degree of geographic heterogeneity in the relative importance of covariate shocks points towards regions where IBLI may be more or less well suited to reducing the covariate risk associated with livestock mortality.

This article links the established work on agricultural index insurance products in higher income economies with the emerging literature on index insurance in developing economies while also providing a benchmark for basis risk that is useful for index insurance products more broadly. Our results underscore the dangers of assuming that cleverly designed financial instruments always perform as advertised. Given the burgeoning interest in index insurance within the development, finance, and agricultural communities, and the glaring dearth of evidence on basis risk in these products, our findings offer a cautionary tale to researchers and practitioners alike.

The rest of the article is structured as follows. We begin with an examination of the components of basis risk in Section 2. Section 3 describes the context, the IBLI product, and data. Section 4 examines the simulated impact that IBLI coverage has on the distribution of outcomes that households face. We then decompose basis risk into its various components in order to reveal which factors drive the product's imperfect performance and which are associated with idiosyncratic losses. We conclude in Section 5 with a discussion of the implications of our findings for IBLI and other index insurance products.

Basis Risk

Multiple factors have led to the current dearth of empirical estimates of basis risk in developing countries. First, longitudinal household data are required in order to identify the distribution of basis risk. Because administrative cost savings from reduced data collection are a key selling point of index insurance, such data are commonly lacking. Second, there are multiple measures of basis risk and it is not obvious which metric is most salient to potential consumers or to which aspects of basis risk insurance providers should pay most attention. To complicate matters further, indemnity payments may improve the net expected outcome while increasing its variance by over-indemnifying losses, which reduces the usefulness of mean-variance analysis, a method commonly used to examine risky choices. Finally, most index insurance policies use an index measured in units fundamentally different from the ultimate objective of insurance – stabilizing wealth or income – as in the case of weather insurance contracts that aim to insure against crop loss; this mismatch significantly complicates the estimation of basis risk.

Tests for stochastic dominance offers one intuitive approach for thinking about the value of insurance and basis risk. Conventional, loss-indemnifying, insurance coverage that is priced to be actuarially fair and has no deductible weakly second-order stochastically dominates no insurance because it transfers resources from periods with good outcomes to periods with poor outcomes at no cost. A similar index insurance contract (i.e., actuarially fair with no deductible) with no basis risk would do the same, intertemporally transferring risk at no cost to weakly stochastically dominate the no insurance alternative.

But such product designs are abstractions from the real world of commercially loaded (i.e., not actuarially fair) policies with deductibles (or, equivalently, non-zero strike levels) and basis risk. If we allow for basis risk, there is no assurance that an index insurance product reduces risk exposure. Due to this positive probability of increases to risk, index insurance does not necessarily weakly second order stochastically dominate the no insurance alternative. That is, a risk averse individual may prefer no insurance over index insurance with the possibility of basis risk, even at actuarially fair premium rates.

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

Since most consumers face loaded premium rates and basis risk is practically inevitable, arguably even optimal given costly data collection, this makes the social value of index insurance an intrinsically empirical question because there exist many contracts with basis risk that could offer valuable risk mitigation services to clients. And, because individuals do not face identical losses, products may be risk increasing for some individuals while for others they are risk reducing. Put differently, index insurance with basis risk might be a targetable product. The welfare effect of index insurance contracts and the distributional profile of those effects among heterogeneous agents are thus also inherently empirical questions. The existing literature has not yet explored these issues.

The remainder of this section develops a framework for examining basis risk. We deviate from the commonly used model for index insurance developed by Miranda (1991) in order to more clearly separate basis risk into its idiosyncratic and design components. Section 4 draws on this framework to empirically examine those components and learn about the factors that contribute to each.

As a stylized example, let individual *i* living in a spatially defined division *d* experience losses in period *t* at rate $L_{i,d,t}$.[2,3] Large scale events such as drought or floods can generate losses across many individuals in the same area. Such covariate losses are reflected in $\bar{L}_{d,t}$, the average or covariate losses in area *d* at time *t.* An individual's losses can then be divided into covariate losses and a remaining idiosyncratic component ($L_{i,d,t} - \bar{L}_{d,t}$).

The variance in loss rates that an individual faces over time ($Var_t[L_{i,d,t}]$) is one metric of risk.[4] Similar to loss rates, an individual's risk can be decomposed into a covariate component, an idiosyncratic component, and the covariance between idiosyncratic losses and covariate losses ($Var_t\left[L_{i,d,t}\right] = Var_t\left[L_{i,d,t} - \bar{L}_{d,t}\right] + Var_t\left[\bar{L}_{d,t}\right] + 2 * cov_t\left[L_{i,d,t} - \bar{L}_{d,t}, \bar{L}_{d,t}\right]$). Therefore, as a household's losses become more similar to those of their neighbors ($L_{i,d,t} \rightarrow \bar{L}_{d,t}$), the risk that they faces reflects covariate risk to greater and greater degrees ($Var_t\left[L_{i,d,t}\right] \rightarrow Var_t\left[\bar{L}_{d,t}\right]$). Alternatively, households that typically experience much less risk than their neighbors face idiosyncratic risk that is larger than their total risk.[5] This points towards a potential population for whom a financial tool designed to indemnify covariate risk may be inappropriate because it would increase the variance of outcomes.

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

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

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

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

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

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

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

An index that tracks average division level losses exactly maximizes total coverage and minimizes basis risk but is unlikely to be achievable or at least generally not cost effective. Differences between the division average and the index are called design errors. The variance in design error, design risk ($Var_t\left[\bar{L}_{d,t} - Index_{d,t}\right]$), is the remaining covariate risk that could theoretically be captured by a (better) division level index (Elabed et al. 2013).

The risk that an insured individual faces can be described by the sum of idiosyncratic risk, design risk, and the covariance between design error and idiosyncratic error:

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

In addition to the magnitude of basis risk, the sign and circumstances of basis error are also likely to be important to consumers. Figure 1 illustrates that point by displaying all of the possible loss-index combinations. The horizontal and vertical axis represent the range of time-specific individual losses ($L_{i,d,t}$) and index values ($Index_{d,t}$), respectively, where both index and losses refer to a loss rate ($L_{i,d,t}, Index_{d,t} \in [0,1]$). The 45° line represents the set of outcomes where the index and losses are identical and basis error is zero. Below the 45° line, losses are greater than those predicted by the index, while above the 45° line, the index predicts higher losses than experienced.

Contracts typically map index values onto indemnity payments in a nonlinear fashion. For example, index insurance generally does not cover all losses. The strike (S in Figure 1) is the value that the index must exceed in order for there to be an indemnity payment, equivalent to a deductible in conventional indemnity insurance. Events during which high losses are suffered but the index remains below the strike level are termed false negatives. False negatives likely damage the reputation of the product because households pay a premium and experience losses that exceed the strike, but none of those losses are indemnified. Analogously, a high index that initiates a payment while the individual losses are less than the strike falls in the false positive region. Although false positive indemnity payments are a windfall for individuals, the payments are not necessarily risk reducing and may perversely transfer money from low to high income states through premiums to fund that windfall.

The outcomes faced by an individual would describe the distribution of $(L_{i,d,t}, Index_{d,t})$ realizations scattered in Figure 1. We are most interested in IBLI's impacts on downside risk during catastrophic events in which losses are beyond the strike. In this case, downside risk is estimated as the semi-variance beyond the strike and downside basis risk is estimated as the semi-variance of shortfalls in indemnity payments, conditional on losses being greater than the strike. The Index Based Livestock Insurance (IBLI) product and IBLI household survey from northern Kenya provide a rare opportunity to examine this basis risk distribution using policy and household data, which are described in the next section.

Background on Kenyan Pastoralists, IBLI and the Data

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

The IBLI pilot started in the Marsabit district of northern Kenya in January 2010. IBLI is an index insurance product based on a remotely collected indicator: the normalized difference vegetation index (NDVI). NDVI is an indicator of the level of photosynthetic activity in observed vegetation and, being a good proxy of the available rangeland forage for animals, should be highly correlated with livestock mortality.[6] The IBLI contract was designed by regressing historic livestock mortality rates on transformations of lagged NDVI data to estimate a seasonal livestock mortality rate response to preceding NDVI observations (Chantarat et al. 2013).[7] The regression approach is appealing because minimizing the residual sum of squared errors is equivalent to minimizing the variance of the difference between the index and individual losses, or basis risk. In addition, the index was developed by relating historic regional environmental conditions to the unconditional regional average loss rates, irrespective of coping strategies, such as herd migration, which would be challenging for environmental models to address.

Division-specific indices are calculated for each of Marsabit's five administrative divisions. During the period considered here, the five divisions were grouped into two contract divisions, upper and lower, each with its own response function. Figure 2 displays the five index (administrative) divisions and how they are allocated into contract divisions. The IBLI strike and deductible are set at 15%.

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

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

The Marsabit region experiences a bimodal rainfall pattern, which naturally produces two insurance seasons per year. Twelve month contracts are sold twice a year, during the two months preceding each insurance contract season (January-February and August-September), so that each twelve month contract covers two indemnity periods. The premium rates are fixed and identical across seasons and within contract regions. See Chantarat et al. (2013) for more detailed information on the IBLI product.

Our analysis uses data from a longitudinal household survey collected annually for four years between 2009 and 2012. The first survey round took place three months before IBLI launched and subsequent rounds took place during the same October-November period each year thereafter. The survey was used to collect data in 16 sublocations in four of the five IBLI pilot divisions, selected to provide a wide variety of market access, agro-ecological zones, ethnicity, and herd size. Within sublocations, 924 households were randomly selected proportional to sublocation population and within herd size strata.

The survey collects data on a wide variety of demographic, economic, and health characteristics but emphasizes livestock herd dynamics.[8]. Because much of this analysis relies on the estimation of household-level estimates of livestock mortality rate, the sample is restricted to the 736 households that are maintained through all 4 survey rounds and that always own at least one livestock. See Appendix A for a discussion of attrition and the sample used in this study.

During the four sales seasons between 2009 and 2012, 429 IBLI purchases are observed in the survey data. Of those purchasers, the mean coverage purchased was 2.6 tropical livestock units (TLUs).[9]

Although IBLI coverage was only available for the last five of the eight insurance seasons captured in these data, all eight seasons are used in this analysis in order to better estimate the risk and basis risk distributions that households face. The first key variable of

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[8] The survey codebook and data are publically available and found at https://livestockinsurance.wordpress.com/publications/

[9] IBLI coverage is sold in tropical livestock units (TLU), which are calculated as follows: camels=1TLU, cattle=0.7 TLU, sheep and goats=0.1 TLU.

interest—household-season livestock mortality rate—is estimated using annual herd size and recall data for month of livestock births, deaths, slaughter, sale, and purchases. Figure 3 illustrates the distribution of within-household average and accompanying stochastic loss rates across the sample. The within-household average loss rates are indicated along the x-axis and by the red dots in the top illustration. Also on the top illustration, each household's dispersion of losses is mapped using vertical blue lines, which show the mean plus/minus one standard deviation of their losses. Note the clear trend in increasing stochastic losses (taller blue lines) with increased average losses (moving to the right on the x-axis). The bottom illustration provides a clearer picture of the distribution of observations across average loss rate space. The dispersion of losses and distribution of average losses indicate that for the majority of households, losses are generally low with an occasional high-loss period.

The second core variable of interest—net mortality rate—is the simulated net outcome of losses, less premium payments plus indemnity payments. There are a number of relevant annual premium rates for IBLI policies: the subsidized rate at which policies were sold during the survey period, the within-sample actuarially fair premium rate, and the loaded and unsubsidized commercial rate calculated by the underwriter. Importantly, the subsidized rates are lower that the within-sample actuarially fair rate in all divisions. A detailed description of the livestock mortality rate estimation process, the various premium rates, and index values are found in Appendix B. Indemnity payments are drawn from the same historic data used in the actuarial calculations by the underwriters.

In the following sections we examine the impact of IBLI coverage on risk and estimate a number of idiosyncratic and design risk metrics in order to provide a clear picture of IBLI's performance. We focus on full insurance rather than optimal coverage because we are specifically interested in learning about the distribution of basis risk and factors that determine where a household falls in the distribution. Fully insured households provide us with the opportunity to examine the factors that are associated with both positive and negative outcomes, be that from poor index design or high idiosyncratic risk.[10] A convenient byproduct of fully insured herds is that net outcomes are in units of livestock mortality/survival rate.[11]

Results

We begin this section by comparing the outcomes without IBLI coverage and the net of losses, premium rates and indemnity payments associated with purchasing coverage. This provides a vantage point by which to better understand the magnitude and heterogeneity in coverage, and thus basis risk, provided by the IBLI product. It is also, to our knowledge, the first article to look at coverage provided by an index product in a low-income country that draws on household level data.

Comparing histograms of the survival rates without IBLI coverage to the net survival rate with IBLI coverage—calculated using commercial premium rates—reveal that IBLI coverage changes the distribution of outcomes dramatically (Figure 4). Most apparent is a significant mass with a greater than one net outcome with insurance, when (by construction) there are outcomes with greater than one livestock biological survival rate.[12] Observations with greater than one net survival rate reflect indemnity payments exceeding the sum of their losses plus the premium.

Notice as well that a small number of observations have moved to the left of zero livestock survival in the insured case. A less than zero net outcome is due to situations in which a premium is paid and extremely high losses are experienced, but very little or no

[10] Because coverage cannot be negative, an analysis of optimal coverage would only include those households for whom IBLI improves outcomes.
[11] At full insurance all calculations can be performed as a ratio of the full herd. The net survival rate on an insured herd is estimated by subtracting seasonal loss rate and premium rates, which are a percentage of herd value, from one, and adding indemnity rates when indemnity payments are made. IBLI places a value of 15,000 KSH for each TLU and premium rates are set at a percentage of that value according to index division (Figure 2).
[12] That is not to say that there are not observations of net seasonal growth to herd size. Herd size increased between seasons in about 32% of the observations. Here, we are examining only the insured risk, which is livestock mortality, not changes to herd size.

indemnity payment is made.[13] Thus, at the population level, there is a small but real chance that an insured household may face a net outcome of less than zero.

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

Let *f(x)* describe the distribution of observed livestock survival rates and *g(x)* describe the distribution of net outcome of fully insuring (i.e., net of premium and indemnity payments). If the insured survival rate distribution first order stochastically dominates (FSD) the uninsured distribution, $F(x) \equiv \int_{-\infty}^{x} f(x)dx \gg G(x) \equiv \int_{-\infty}^{x} g(x)dx$, then insurance dominates remaining uninsured under the very mild assumption of local nonstationarity. Figure 5 shows that the insured distribution does not FSD the uninsured state. In particular, as shown in the right panel of Figure 5, which focuses on just the left tail of the distribution depicted in the left panel, no insurance dominates insurance when households experience extremely high losses and do not receive indemnity payments greater than the premium. Indeed, the insured distribution necessarily fails to stochastically dominate the uninsured case at any degree of stochastic dominance because of the positive probability of negative net survival rates under insurance due to catastrophic losses with little or no indemnity payment.

Distribution Metrics—The mean-variance method for analyzing choices under risk is common in the insurance literature. For example, Miranda (1991) defines the change to

[13] In 16 of the 5,888 observations, households experienced less than zero net livestock survival rate due to premium rates being added to an already high livestock mortality rates. The minimum net outcome is -2.12% of the original herd value.

yield risk due to insurance as the variance in yield without insurance less the variance of the net yield, which includes premiums and indemnity payments. This approach is intuitive and requires the estimation of very few parameters, allowing for more powerful household level analysis than does testing for stochastic dominance, and is consistent with expected utility as long as mean and variance are sufficient for describing differences in outcomes (Meyer 1987). But insurance may lead to changes beyond those that are captured by mean and variance, so that mean—variance analysis is inconsistent with important classes of preferences. For example, risk averse individuals may distinguish asymmetrically between deviations from the mean due to extremely good outcomes and extremely poor outcomes (Alderfer and Bierman 1970). Agricultural insurance products specifically target those negative outcome events rather than all variation (Turvey 1992). Higher moments (beyond mean and variance) can be calculated to examine changes to distributions that are not symmetrical while semi-variance analysis examines changes to downside risk.

To examine the impact of insurance on mean, variance, and skewness, we first estimate the eight-season, within-household statistics, and then estimate the weighted average of each statistic across the sample.

Loaded and unsubsidized insurance are unlikely to be mean preserving or improving, since it is priced above the actuarially fair level. Comparing the expected net outcome of being insured with the uninsured case shows that the loading indeed results in a net decrease in survival rates by about 1.1% (t-stat=18.66, Table 1).

But the primary motivation for purchasing insurance is presumably not to increase expected outcomes but to reduce the risk of extremely poor outcomes. In this case, the average variance with insurance is slightly greater (2.3%, t-stat=1.89, Table 1) than without. This is not surprising as the domain of potential outcomes has increased for insured households and we expect over-indemnification to also contribute to outcome variance. The histograms of outcomes (Figure 4) suggest that IBLI impacts the downside risk that households face via indemnity payments that shift outcomes to the right. Analysis of skewness supports that hypothesis. Distributions are negatively skewed in both the uninsured and insured cases, but insurance significantly reduces the skewness magnitude, by 37.6% (t-stat=16.01, Table 1). The skewness values indicate that the impact of IBLI is not a symmetric contraction of the variance. Rather, IBLI reduces the likelihood of large shocks at a small cost to expected outcomes, as is to be expected from a loaded insurance product.

The welfare impacts of an increase to variance is not clear in this case, as it is the result of both under- and over-indemnification of losses. Downside risk, or the risk a household faces associated with losses beyond the strike, is unencumbered by such ambiguity and can be estimated as the semi-variance beyond the strike (Turvey 1992). Downside risk is calculated by $\frac{1}{T-1}\sum_{t=1}^{T}(O_{it}-\dot{O}_t)^n I(Z_{it}))$ where O_{it} is the outcome experienced by individual i in time period t, $T=1,2,\ldots,8$, $\dot{O}_t$ is the target, n is the weight given to deviations from the target, and $I(Z_{it})$ is an indicator function that is equal to one if a condition is met and equal to zero otherwise.

In this case, the outcome under examination is livestock mortality rate and the indicator function is used to identify severe events, defined as those seasons in which the household experienced at least 15% livestock mortality.[14] The target is used to reference the magnitude of the shock, which we set to the strike in order to capture the risk beyond the strike, associated with those extreme losses. Therefore, the set of metrics are the average sum of the distance between outcome and strike with distance weighted by n. Because the distance measure is not in relation to the mean, as it is with variance, the addition of a constant premium rate affects this measure of downside risk. This is important as risk coverage is often discussed quite separately from premium levels. To explore the effects of premium levels on downside risk we include estimates of downside risk for the subsidized, within-sample actuarially fair, and commercial, unsubsidized rates.

Setting $n=1$ provides an estimate of the expected losses beyond the strike. The expectation of the outcome will rest on the level of loading or subsidy applied to the

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

premium and the timing of the indemnity payments. If indemnity payments are *perfectly* made during high loss events, households with insurance could experience an improvement to expected conditional losses even at the commercially loaded premium rate. Conversely, if the product is not making payments during the high loss events we could see an increases in expected net losses even at subsidized rates. The estimates indicate the index is performing somewhere between those two boundary outcomes, triggering indemnity payments during seasons with high losses enough of the time to statistically significantly improve expected outcomes at the subsidized and actuarially fair premium rates, but not enough to overcome the additional 40% loading of the commercial rates (Row 1, Table 2).

Semi-variance around the target is estimated by setting $n = 2$. As with the conditional expected losses, the estimates indicate that the benefits associated with reductions to semi-variance during severe events are very sensitive to the premium levels (Row 2, Table 2). At the commercially loaded rate, the average household's semi-variance remains about the same with or without IBLI, but at the actuarially fair rate or subsidized rate households are, on average, better off with IBLI coverage. It worth noting that perfect loss-indemnifying insurance above 15% would drive both the expected losses above 15% and the semi-variance above the strike to zero. But, perfect index insurance would not cover all losses above the strike unless all individuals within the covariate region suffer from identical losses at all times. For example, 49.2% of the non-zero observations used in Table 2 (experiencing livestock mortality rate>0.15) occurred during periods when covariate losses were below 0.15, and thus fall outside the parameters of the IBLI contract. We examine the index design and idiosyncratic contributions towards this remaining basis risk, represented by the semi-variance here, in Section 4.

On average, IBLI sold at the commercially loaded premium rate significantly reduces expected survival rate net of premium payments but also adjusts the distribution to one more favorable to the household as indicated by a significant reduction in skewness. Restricting the analysis to those periods when households experience greater that 15% livestock mortality reveals that the benefits of IBLI coverage on downside risk are highly sensitive to the premium rates and are positive at the actuarially fair rates. Yet, the impact of IBLI is likely to be heterogeneous across loss rates, premium levels, and households, so that while many households may benefit from IBLI, many others may not. For example, IBLI coverages reduces variance for 42.3% of the sample, skewness for 81.5%, and downside risk is improved for 41.9% and 62.4% of the sample at the unsubsidized and subsidized rates, respectively (Table 3). At any of the relevant either premium levels, many households experience benefits as measured by one metric and net costs by another. Only a utility framework could fully order outcomes, but we hesitate to introduce an additional set of (questionable) model assumptions about households' preferences.

This section examined the impact that IBLI coverage has on the distribution of household outcomes. There is a great deal of heterogeneity between household outcomes and across metrics. It is clear that the benefits of IBLI are far from universal in magnitude or even sign. Put differently, product value varies remarkably within the sample and as a function of the premium rate charged for the product. The next section examines basis risk at the household level to determine which factors contribute it and thus to the benefits, if any, of IBLI.

Decomposing Basis Risk

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

Table 4 summarizes the downside risk without insurance and the downside basis risk associated with index shortfalls during high loss events. Downside risk is estimated as the semi-variance of livestock mortality rate beyond the strike and downside basis risk is estimated as the semi-variance of the difference between livestock mortality rates and the indemnity rate, conditional on the household experiencing high livestock mortality rates (>0.15) and a shortfall in indemnity rates. This focuses the analysis on those periods when households suffer severe losses and on IBLI's performance in reducing risk caused by such losses. The overall average reduction to squared deviations from the strike during high loss events due to IBLI coverage is about 28.4%.

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

Figure 6 plots the 32 index-covariate loss observations on the domain described by Figure 1. Fitted lines above and below the strike are also included, along with confidence intervals. There is clearly large variation across the sample in how well the index performs. Below the mortality rate equivalent of the strike (to the left of the vertical red line), most of the fitted line lies above the 45 degree line, reflecting frequent over predictions by the index when division level mortality rates were actually quite low. Above the mortality rate equivalent of the strike (to the right of the vertical red line), the index generally understates covariate losses. In total, there are eight (25%) observed false positives and four (12.5%) false negatives. The high rate of discrete error observed on an index designed explicitly to minimize basis risk and tested out-of-sample using a data set other than the design data (Chantarat et al. 2013) serves as a strong caution against overconfidence in the quality of index insurance products.

To examine the accuracy of the index we focus on those events when covariate losses were greater than the strike (to the right of the horizontal red line in Figure 6). Table 5 provides summary statistics of the covariate and design risk associated with those events. The covariate risk associated with severe events represents only 17% of the average downside risk estimated in Table 4, foreshadowing the large role that idiosyncratic risk plays.[15] Design risk is then calculated as the semi-variance of the shortfall of the index during those covariate events. Notice that the average conditional design risk represents less than 10% of the average conditional basis risk presented in Table 4. The precision is an estimate of the portion of downside covariate risk that the index successfully covers. On average, the index reduces downside covariate risk by about 63.2% but there is significant heterogeneity in covariate risk and index precision between divisions.

Regressing the index onto covariate losses shows that there are systematic differences between the index and covariate losses (Table 6). The point estimate for covariate losses—0.377—from the unconditional regression (Table 6, column 1) reflects that the index generally underpredicts losses when covariate losses are low and overpredicts losses when they are high. Coincidentally, the switch from over to under prediction to over prediction takes place when covariate losses are equal to 0.212, near the strike of 0.15. Testing the coefficients against the null hypothesis of a perfect index product ($\alpha_d = 0\ and\ \delta_d = 1$), reveals an imperfect structural relationship between the index and covariate losses that could be reduced by shifting and rotating the index.

As a check for performance during only the large covariate shocks that IBLI is intended to mitigate, the regression is restricted to season-district observations during which covariate losses are above the strike. There are only fourteen such observations, so the estimation results should be interpreted carefully. During these large covariate shocks, there continues to be evidence of structural differences between the index and covariate losses (F-stat=7.64). But those structural differences could be mostly addressed by adjusting the index upwards, while the slope of the index is statistically indistinguishable from the ideal—one (F-stat=1.52).

In addition to adjusting the index, a second potential approach to reducing design risk is to adjust the strike. Calculating design error conditional on covariate losses greater than

[15] Notice that IBLI coverage is reducing exposure to risk from extreme events at an average rate (28.4%) that is greater than the average share of risk that is associated with large covariate shocks (17%). That is because the IBLI index predicts catastrophic losses in a number of periods during which covariate losses are below the strike (15%) but when there is a subsample with high losses.

the strike and allowing the strike to vary across the interval [0,0.25], we examine how well the index predicts covariate losses above the strike at various strike levels. We find that varying the strike rate has no significant impact on the accuracy of the index; there is a great deal of variation in design error at all strike levels (Figure 7).

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

Idiosyncratic Risk—A second and far larger portion of downside basis risk arises due to idiosyncratic losses, or mortality not reflected in the division average, or covariate, losses. Although much idiosyncratic loss is likely associated with random events, they may also have a systematic relationship with household or geographic characteristics. If such patterns are known to prospective purchasers, a form of adverse selection subtly returns even though index insurance is pitched in part as an approach to obviate adverse selection problems in conventional insurance. This sort of adverse selection does not necessarily affect equilibrium pricing or profits of the insurance. But if insurers pool actuarial estimates across seasons and/or contract regions, as was the case with IBLI during this period, consumers face (inadvertent) heterogeneity in premium subsidies/loadings and the resulting patterns or demand do pose a threat to insurer profits.[16] We now examine factors associated with idiosyncratic risk.

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

Figure 8 shows the ratio of covariate risk to average total risk at various geographic scales of aggregation.[17] This ratio captures the risk faced by households that could be covered by an index product at each covariate scale in this setting. The average ratio of covariate to total risk nearly triples as the covariate area shrinks from a large aggregate region composed of a single IBLI division, to 16 separate divisions defined by sublocation. There is also a great deal of variance between sublocations. Covariate risk within sublocations is less than 15% of total risk in four survey sublocations, while it is greater than 50% in three. In those locations with very low covariate risk, even a local and extremely accurate (i.e., zero design risk) index product could not cover much of the risk that households face. On the other hand, households in other many survey sublocations face a great deal of covariate risk, making them prime candidates for index insurance.[18]

There is also variation among households and even within households over time. In this final analysis of basis risk patterns, we explore which factors are associated with

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[16] Pooling index regions into a single premium region introduces cross-subsidies between index regions. The same is true if premiums are not adjusted to account for seasonal-specific risks. See Jensen, Mude and Barrett (2016) for more discussion on adverse selection associated with index products.

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

[18] It is possible that the differences in average covariate risk share are related to variation in the shapes and sizes of the sublocations. But regressing the sublocation average ratio of covariate risk to risk on sublocation area and the ratio of area to perimeter yields no statistical evidence of such a relationship. Results of that analysis are available upon request.

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

Spatial correlation of idiosyncratic risk is clearly large (Figure 8) and could arise due to local environmental shocks or spatially correlated household characteristics. Although we cannot fully disentangle the two here, we can examine household characteristics for explanatory value with and without sublocation fixed effects, in order to reveal when factors are important due to between-sublocation variation and within-sublocation variation. Sublocation fixed effects alone are able to account for a fairly large portion of variation in downside idiosyncratic risk between households (R^2=0.125, column 4, Table 7) but very little of the variation in idiosyncratic losses (R^2=0.026, column 1, Table 7). Indeed, household characteristics do no better in explaining idiosyncratic losses or downside risk than do sub-location fixed effects as revealed by comparing columns 1 with 2, and 4 with 5 in Table 7. Including both controls for sublocation fixed effects and household characteristics provides the best fit, the R^2 is nearly the sum of those from the considering location and household characteristics separately indicating that the two processes are fairly distinct (columns 1 and 2 vs. 3, and columns 4 and 5 vs. 6).

The ratio of income generated from livestock is the only livestock-related characteristic that is consistently (negatively) associated with idiosyncratic risk, even when we control for sublocation fixed effects. There does seem to be a weak relationship between herd size and exposure to idiosyncratic risk, the average marginal effect of herd size is negative and statistically significant in the analysis presented in Table 7 columns 3 and 6, and the third order polynomial coefficients estimates are jointly statistically significant Table 7 (analysis not included). Households with relatively more dependents also have greater idiosyncratic risk.

What is perhaps the most striking finding of this analysis is how little idiosyncratic risk is associated with household characteristics or can be captured by sublocation fixed effects. Idiosyncratic losses cannot be very well explained by sublocation average losses nor by a host of household characteristics that could reasonably be associated with livestock mortality rates. Idiosyncratic losses seem to be almost entirely random while variance in losses is much more predictable, but still more than 75% of the variation in semi-variance is unexplained by readily observable household characteristics and sub-location fixed effects, as might be practical for targeting purposes.

As a robustness check, we estimate a fixed effects model to determine if unobserved time-invariant household characteristics drive our findings. Only column (2) from Table 7 can be estimated in this way because the within-household variation in sublocation is nearly zero and semi-variance of idiosyncratic losses has no within household variance. In addition, risk aversion, age, and gender variables are dropped due to lack of within household variation. The fixed effects model reported in Appendix D also captures very little of the rate of idiosyncratic losses and there is little indication that those losses are anything but random.

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

Discussion

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

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

Given the burgeoning interest in index insurance within the development, finance, and agricultural communities, and the glaring dearth of evidence on basis risk and therefore product quality, our findings offer a cautionary tale to researchers and practitioners alike. They illustrate the complexity of providing index insurance, even in an environment that in some respects seems ideal. Our results highlight the spatial sensitivity of covariate risk to the covariate region and the resulting prospect for spatial adverse selection in demand patterns. We find that basis risk, especially idiosyncratic risk, is substantial, pointing towards the continued importance of informal risk sharing agreements and other complementary risk management mechanisms even when index insurance is available. An optimally designed index insurance product yields risk-reduction for many prospective purchasers but offers far-from-full coverage. Caution seems warranted in the wholesale promotion of index insurance as a risk management instrument for low-income populations underserved by conventional insurance markets.

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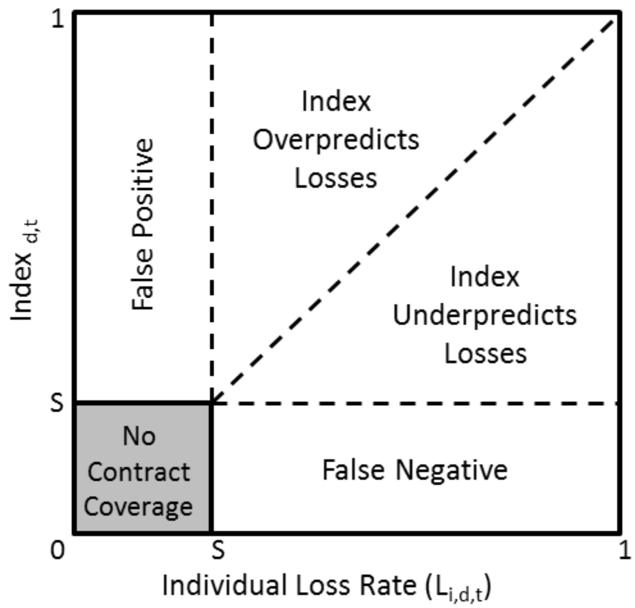


Figure 1. The Domain of Basis Error

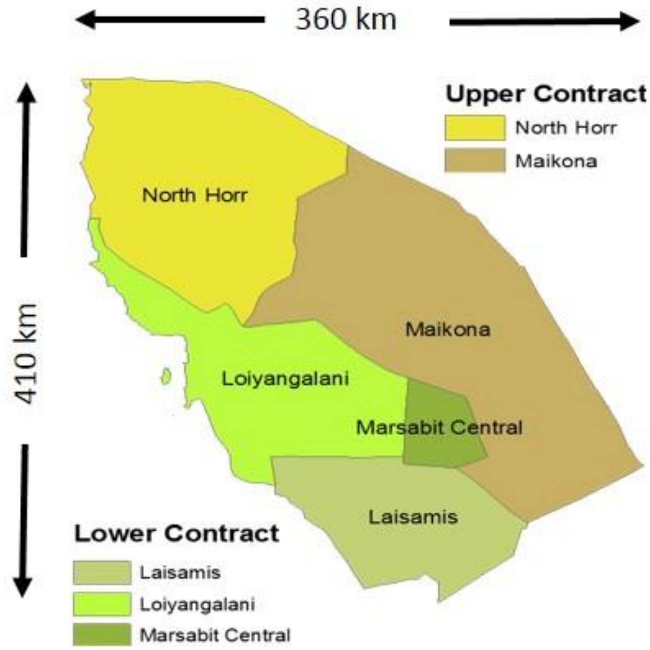


Figure 2. IBLI Geographical Coverage and Index Divisions

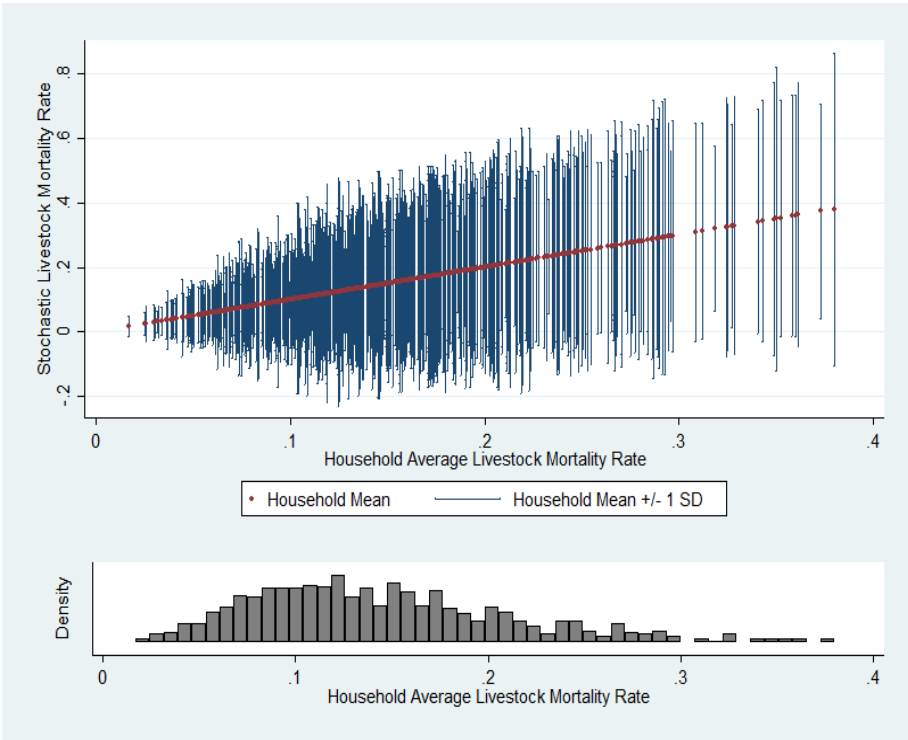


Figure 3. Distribution of Within-Household Average and Stochastic Losses

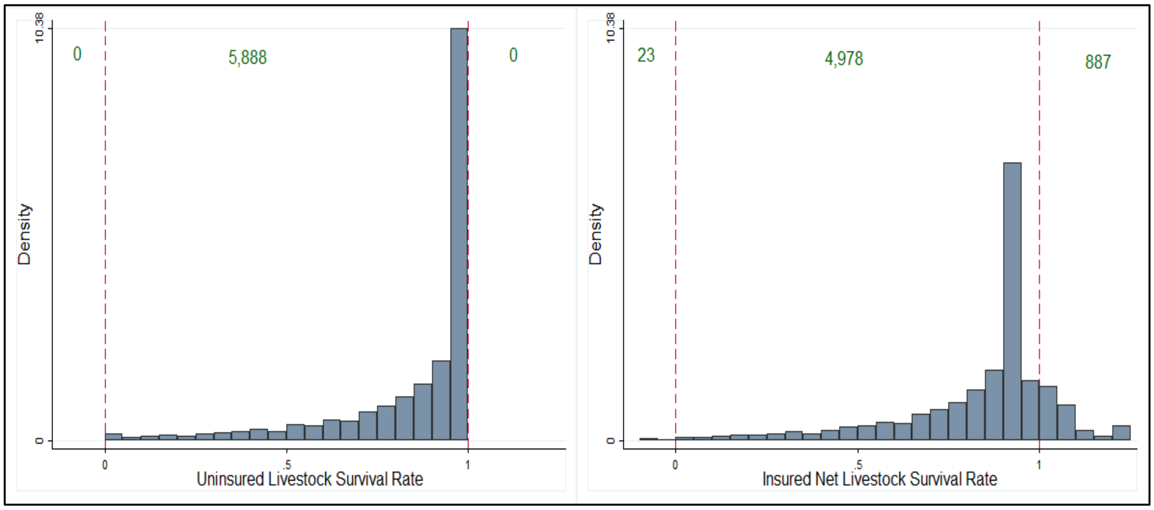


Figure 4. Histograms of Livestock Survival Rate and Net Survival Rate with Full Insurance

Notes: Net livestock survival rate with full insurance equals the household's seasonal survival rate less the commercial premium (loaded and unsubsidized) plus indemnity payments. Tally of observations to the left of zero, between zero and one, and to the right of one are in green.

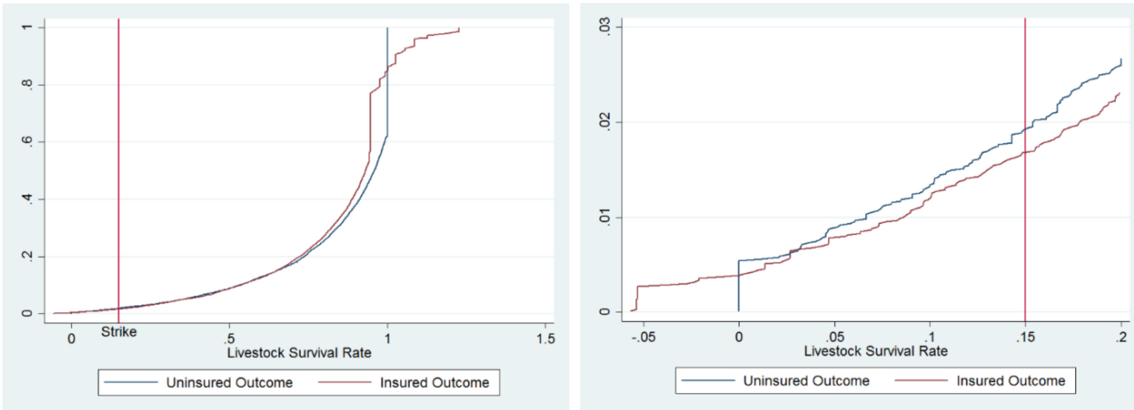


Figure 5. Cumulative Distribution of Livestock Survival Rate and Net Outcome:

Full Cumulative Distributions (Left) and Left Tail of the Cumulative Distributions (Right)

Notes: Insured livestock survival rate equals the household's seasonal survival rate less the commercial premium (loaded and unsubsidized) plus indemnity payments.

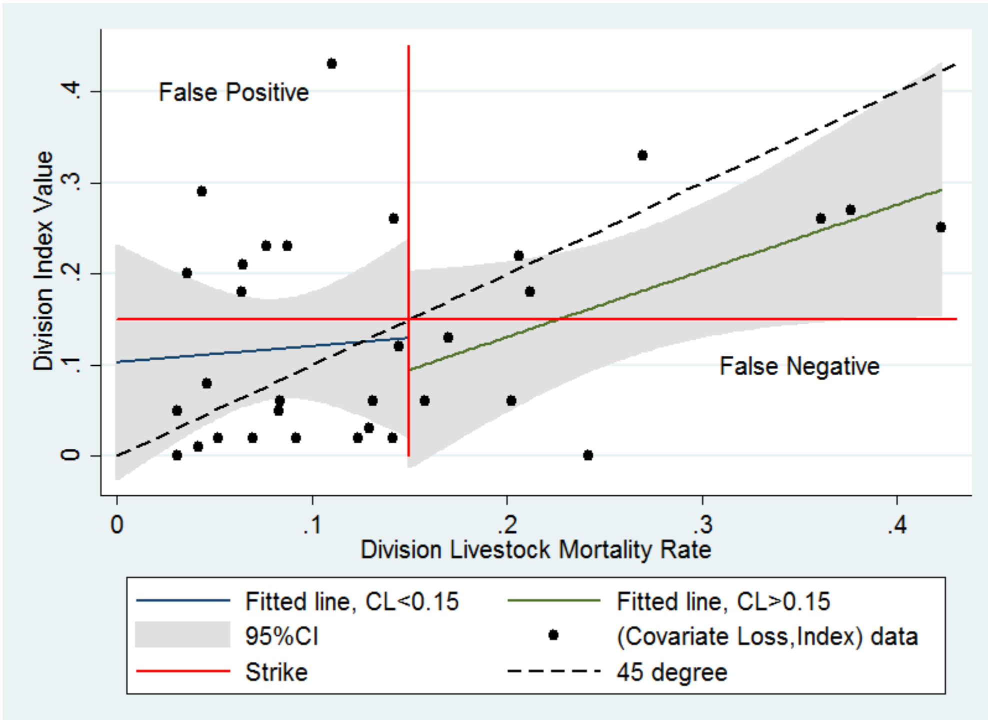


Figure 6. Design Error Above and Below the Strike (0.15)

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

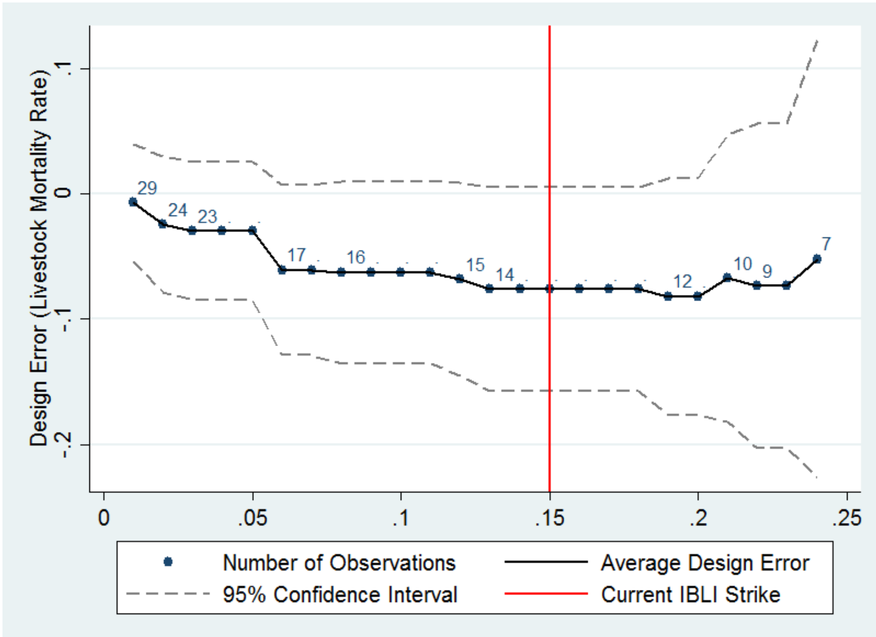
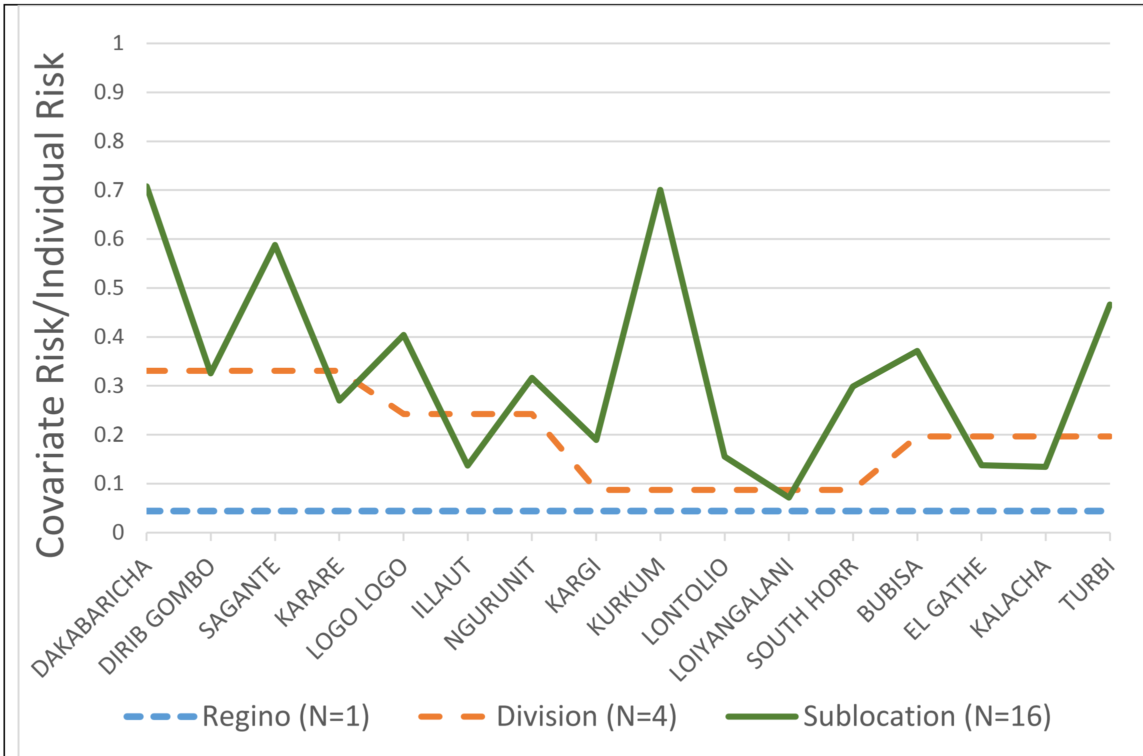


Figure 7. Index Accuracy at Across Covariate Loss Strike Levels



	Entire Sample	Division	Sub-Location
Risk (R) x 100	4.41	4.86	5.29
Covariate Risk (CR) x 100	0.54	1.12	1.87
Ratio (CR/R)	0.12	0.21	0.34

Figure 8. Ratio of Covariate Risk to Individual Risk at Different Geographic Scales

Table 1. The Average Within-Household Mean, Variance, and Skewness of Survival Rate With and Without IBLI Coverage

Statistic	Uninsured	Insured	Difference	Standard Error	t-statistic
Mean x 100	85.0	84.0	0.929	0.050	18.66***
Variance x 100	5.08	5.19	-0.117	0.062	-1.89*
Skewness	-1.18	-0.735	-0.444	0.028	-16.01***

Notes: Analysis uses the commercial premium rate.

Table 2. Downside Risk during Severe Events (Mortality Rate > 0.15) With and Without IBLI Coverage

Statistic	Premium[1]	Uninsured[2]	Insured[2]	Difference[2]	t-statistic
Expected Losses > 0.15	Commercial	9.49	9.70	-0.21	-3.25***
	Actuarially Fair	9.49	9.32	0.17	3.16***
	Subsidized	9.49	8.54	0.96	17.37***
Semi-Variance	Commercial	4.33	4.38	-0.042	-0.82
	Actuarially Fair	4.33	4.16	0.17	3.86***
	Subsidized	4.33	3.73	0.60	12.52***

Notes: [1]The weighted average annual premium rates are as follows: commercial=10.8%, actuarially fair=8.6%, subsidized=3.8. [2] Values are multiplied by 100.

Table 3. Proportion of Households for Whom IBLI Improves Their Position with Respect to Each Statistic

Statistic	Proportion		
	Loaded & Unsubsidized	Actuarially Fair	Subsidized
Mean	0.266	0.456	1.000
Variance	0.423	0.423	0.423
Skewness	0.815	0.815	0.815
Semi-Variance	0.419	0.479	0.624

Table 4. Average Downside Risk without Insurance and Remaining Downside Basis Risk with Insurance in Periods with High Losses

	Central	Laisamis	Loiyangalani	Maikona	Overall
Conditional Losses[1]	0.505	0.427	0.3890	0.381	0.412
Conditional Index[1]	0.204	0.165	0.126	0.156	0.151
Downside Risk (X100)[2]	6.000	4.661	4.364	2.962	4.329
Downside Basis Risk(X100)[2]	4.337	3.529	3.904	2.032	3.426
Coverage[3]	0.363	0.319	0.176	0.375	0.284
Observations	157	109	247	223	736

Notes: The statistics in the table are the average of household-level estimates. [1] Conditional losses and index values are the average index and livestock mortality rates from the pool of household observations with greater than 15% livestock mortality rate. [2] Conditional (downside) risk is estimated using semi-variance of losses beyond the strike, conditional on covariate losses being greater than the strike. Conditional basis risk is calculated as the semi-variance of index shortfalls, conditional on covariate losses being greater than the strike. [3] Coverage is the average of household-level estimates (not the ratio of averages) of reduction in downside risk due to insurance coverage.

Table 5. Covariate and Design Risk in Seasons when Covariate Losses Were Above the Strike

	Central	Laisamis	Loiyangalani	Maikona	Overall
Conditional Covariate Losses[1]	0.392	0.228	0.207	0.255	0.262
Conditional Index[1]	0.255	0.170	0.120	0.165	0.176
Downside Covariate Risk(X100)[2]	1.686	0.771	0.091	0.318	0.717
Downside Design Risk(X100)[2]	0.565	0.163	0.051	0.116	0.224
Precision[3]	0.665	0.788	0.439	0.636	0.632
Seasons w/ mean loss>0.15	2	4	2	2	10

Notes. The statistics in the table are the average of division-level estimates. [1] Division average rates for seasons during which the covariate losses are greater than 0.15. [2] Downside covariate risk is estimated as the semi-variance of covariate losses, conditional on covariate losses being above the strike. Downside design risk is estimated as the semi-variance of the positive difference between covariate losses and the index, conditional on covariate losses being above the strike. [3] Precision is the average ratio (not the ratio of the averages) of conditional covariate risk captured by the index.

Table 6. The Relationship between Covariate Losses and the IBLI Index

	Index	Index (Conditional on CL>0.15)
Covariate Losses	0.377**	0.694**
	(0.180)	(0.248)
Constant	0.080**	-0.012
	(0.033)	(0.065)
F-stat: $H_0: \alpha_d = 0$ and $\delta_d = 1$	6.21**	7.64**
F-stat: $H_0: \delta_d = 1$	11.99***	1.52
Observations	32	14
R-squared	0.127	0.394

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

Table 7. Factors that Contribute to Idiosyncratic Risk

	Idiosyncratic Loss Rate (IL)			Semi-Variance(IL)*		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Male		-0.0182**	-0.0075		-0.0062	-0.0038
		(0.0086)	(0.0086)		(0.0043)	(0.0040)
Dependency ratio		0.0658**	0.0493**		0.0457***	0.0360**
		(0.0258)	(0.0246)		(0.0141)	(0.0140)
Asset index#		-0.0209	-0.0750		0.0391	0.0420
		(0.0743)	(0.0899)		(0.0521)	(0.0625)
Asset index squared#		-0.0114	0.2231		-0.2532	-0.2574
		(0.3345)	(0.3660)		(0.1819)	(0.2025)
HSNP participant		0.0047	-0.0064		-0.0039	-0.0089*
		(0.0089)	(0.0098)		(0.0046)	(0.0054)
Ratio herd camels		-0.0036	0.0089		-0.0039	0.0160
		(0.0227)	(0.0244)		(0.0178)	(0.0202)
Ratio herd cattle		-0.0050	0.0036		0.0025	0.0095
		(0.0186)	(0.0180)		(0.0207)	(0.0259)
Herd size (TLU/100)		0.0192	-0.1161*		-0.0258	-0.1356**
		(0.0534)	(0.0627)		(0.0559)	(0.0600)
Herd size^2 (TLU^2/100^2)		-0.0335	0.0777		0.0873	0.2583**
		(0.0664)	(0.0743)		(0.1076)	(0.1089)
Herd size^3 (TLU^3/100^3)		0.0032	-0.0212		-0.0428	-0.1169**
		(0.0170)	(0.0193)		(0.0505)	(0.0497)
Ratio income from livestock#		-0.0234**	-0.0223*		-0.0374***	-0.0278*
		(0.0111)	(0.0127)		(0.0102)	(0.0151)
Log (1+Savings)#		0.0010	0.0016		-0.0016**	-0.0012
		(0.0014)	(0.0016)		(0.0007)	(0.0011)
Social groups (count)#		-0.0046	-0.0035		-0.0055	-0.0042
		(0.0059)	(0.0064)		(0.0034)	(0.0037)
Moderately risk averse		-0.0110	-0.0071		-0.0024	-0.0001
		(0.0086)	(0.0070)		(0.0050)	(0.0041)
Extremely risk averse		-0.0048	-0.0076		0.0015	-0.0006
		(0.0095)	(0.0079)		(0.0050)	(0.0044)
Sublocation Fixed Effects	Yes	No	Yes	Yes	No	Yes
F-stat: Sublocation FE=0	6.74***		3.86***	4.39***		3.80***
Observations	5,888	5,120	5,120	736	736	736
R-squared	0.026	0.012	0.032	0.125	0.117	0.208

Notes: Regressions include age and age squared of household head, household size, and an intercept term. *Semi-variance of idiosyncratic losses regressed onto the eight-season mean of household covariates. #Variable is lagged by one period in the idiosyncratic losses estimation. Household clustered-robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

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Appendix A: Attrition and Selection Analysis

The level of sample attrition is less than 4% per year; 37 households between first and second rounds, 30 between second and third rounds, and 25 between third and fourth rounds. There are statistically significant differences between the survey households that exit and those that remain in the survey (Table A.1). Households that leave the survey are larger, consume less per person, and generate a greater portion of income from livestock related activities. About 12% of the remaining households are dropped because they have periods with zero reported livestock so that their livestock mortality rate is undefined. The dropped households are similar to the exit households but also have significantly lower education, greater herd size and income than the control households.

Table A.1. Balancing Table (2009: Unbalanced vs. Balanced Panel)

Variable	Maintained [1] (N=736)	Exit, or Dropped	Difference	T-statistic	
Exit households (N=92[2])					
Max education[3]	4.31	4.74	-0.43	-0.88	
Household members (count)	5.76	4.89	0.87	3.38	***
Dependency ratio[4]	0.62	0.59	0.02	0.96	
Consumption per capita (KShs)	1,377	1,736	-360	-2.76	***
TLU owned[5]	19.71	16.14	3.57	1.28	
Income (KShs)	5,259	3,504	1,755	1.01	
Ratio of income form livestock	0.56	0.30	0.26	3.54	***
Risk category[6]	2.49	2.65	-0.16	-0.84	
Savings (KShs)	6,893	13,795	-6,901	-0.98	
Households with zero livestock holdings in at least one period (N=96)					
Max education[3]	4.31	5.28	-0.98	-2.03	**
Household members (Count)	5.76	4.79	0.97	3.87	***
Dependency Ratio[4]	0.62	0.62	-0.01	-0.23	
Consumption per capita (KShs)	1,377	1,989	-612	-4.68	***
TLU owned[5]	19.71	4.30	15.41	5.78	***
Income (KShs)	5,259	5,258	1.29	0.00	
Ratio of income form livestock	0.56	0.08	0.48	9.33	***
Risk category[6]	2.49	2.73	-0.23	-1.28	
Savings (KShs)	6,893	5,217	1,676	0.26	

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

Appendix B: Livestock Mortality Rate, IBLI Premium Rates and Index Values

The ideal estimate of seasonal livestock mortality rate is the ratio of animals entering a season that die during the season. But the data do not allow for tracking specific animals through the season so we construct an alternative estimate of seasonal livestock mortality rate. The numerator of this alternative estimate is the sum of monthly losses ($M_{i,d,m}$) for individual i in division d during month m for all months that fall into season s. The denominator is composed of the sum of the herd size at the beginning of the season ($H_{i,d,start}$) and all monthly additions to the herd over the following season ($\sum_{m\in s} A_{i,d,m}$).[19] Thus, seasonal livestock mortality rates ($L_{i,d,s}$) are estimated by dividing the season's cumulative livestock mortality by the total herd owned by each household that season (Equation B.1).[20]

(B.1)
$$L_{i,d,s} = \frac{\sum_{m\in s} M_{i,d,m}}{H_{i,d,start} + \sum_{m\in s} A_{i,d,m}}$$

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

Average mortality rates vary widely between the four study divisions and across seasons (Figure B.1). More importantly for this analysis, there is clear evidence of large covariate losses within divisions, as is revealed by seasons with high average mortality rates. IBLI can only be an effective risk mitigation tool if catastrophic losses are correlated between individuals. An ideal IBLI product would indemnify those (average) losses that are above the strike (0.15) in Figure B.1.

[19] $H_{i,d,start}$ is calculated using reported herd sizes at the time of the survey and iterating backwards, adjusting for monthly birth, death, purchase, sale, and slaughter. Herd size is constrained by $0 \leq H_{i,d,m}\ \forall\ i,d,m$ to address errors in recall that occasionally lead to erroneous negative livestock herd size estimates.

[20] We rely on estimates of livestock mortality rate because the data does not track individual livestock through each season. The qualitative results presented in this article are robust to using an alternative method for calculating livestock mortality rate, which is described and used in Chantarat et al. (2013).

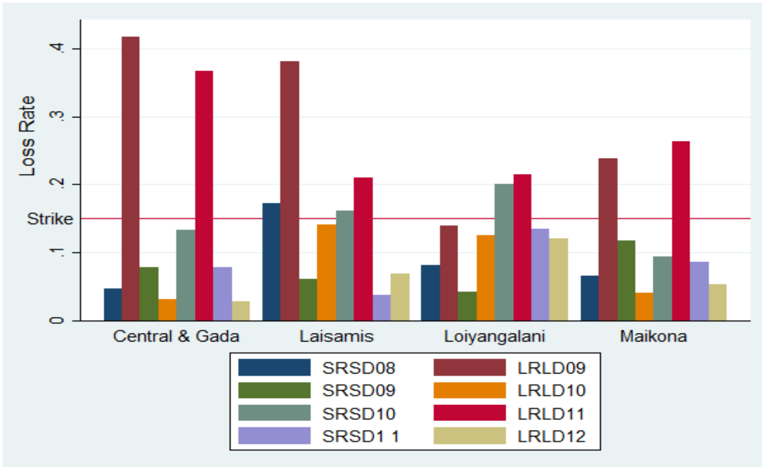

Figure B.1. Division Level Average Livestock Mortality Rate Across Seasons

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

There are three important premium rates to consider for IBLI (Table B.1). The subsidized rates that were made available to pastoralists during the periods covered by this analysis offer insight into the conditions that the survey households actually faced during these periods. The within-sample actuarially fair premium rates provide the best estimates, however, if the intent is to focus on the intertemporal smoothing effect of insurance. Finally, the unsubsidized loaded annual premium rates calculated by the insurance providers in 2014, provide information on outcomes associated with commercially sustainable, unsubsidized premium rates. These final rates reflect a reevaluation of the expected indemnity payments in 2014 in response to severe conditions between 2009 and 2013. Notice that the premium rates are no longer common in the upper and lower contract divisions as of 2014.

Table B.1. Annual Premium Rates in Percent of Insured Value

	Subsidized Rates[1]	Within-Sample Actuarially Fair Rates	Unsubsidized & Loaded Commercial Rates
Central	3.325%	9.25%	10.60%
Laisamis	3.325%	7.50%	11.30%
Loiyangalani	3.325%	7.00%	9.20%
Maikona	5.500%	12.25%	10.70%

Note: [1] The subsidized rates were available to pastoralists form January 2010-January 2012.

This research includes analysis of basis risk before IBLI was available for sale. In those non-sale periods, there are no publically available index values. In the seasons before LRLD 2010, index values were collected from internal program documents: “IBLI Pricing 2010” (SRSD 2008 LRLD 2009 and SRSD 2009) and “IBLI Marsabit Pricing June 2012” (LRLD 2010). The remainder (SRSD 2010 though LRLD 2012) were collected from the publically available IBLI index archive available at http://livestockinsurance.wordpress.com/ibli-kenya/mortality-index-update/index-archive. The indemnity payments represent a percentage of the value of the insured asset and are calculated according to the IBLI contracts (max (index-0.15, 0)).

Table B.2. IBLI Index Values and Imputed Indemnity Payments

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

Note: [1]IBLI was not sold during these seasons.

Appendix C: Household Variables and Summary Statistics

Table C.1. Household Characteristics Used to Examine Idiosyncratic Risk

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

Table C.2. Summary Statistics of Household Characteristics (N=735)

	Mean	Std. Dev.	Min	Max
Idiosyncratic Losses	0.00	0.20	-0.42	0.95
Semi-Variance of Idiosyncratic Losses	0.035	0.036	0.001	0.230
Male	0.64	-	0	1
Age of household head	48.07	18.13	18	99
Number of household members	5.66	2.17	1	19
Dependency ratio	0.60	0.20	0	1
HSNP participant (=1 if true)	0.25	-	0	1
Ratio of herd: camels	0.29	0.30	0	1
Ratio of herd: cattle	0.33	0.31	0	1
Herd size (TLU)	15.3	20.1	0	344.1
Income (Ksh/month)	7,276	11,990	0	236,000
Ratio income from livestock	0.69	0.42	0	1
Savings (Ksh)	3,810	35,100	0	1,515,000
Asset Index	-0.19	0.79	-0.94	5.69
Number of social groups	0.59	0.82	0	6
Extremely Risk Averse (=1 if true)	0.25	-	0	1
Moderately Risk Averse (=1 if true)	0.47	-	0	1
Risk Neutral/Low Risk Aversion (=1 if true)	0.29	-	0	1

The asset index is constructed using factor analysis of a list of important household assets and characteristics in the spirit of Sahn and Stifel (2000). Included are counts of assets that fall into very small, small, medium, and large assets. Small, medium, and large categories are also each divided into two categories according to use (e.g., productive vs. other). There are also indicators of water source, household construction, lavatory facilities, fuel sources, education, cash on hand, land holdings, poultry, and donkeys. Cattle, camels, goats, and sheep are not included in the index as they are captured directly in herd size. The factor loadings are found in Table C.3.

Table C.3. Factor Loadings Estimated by Factor Analysis and Used to Generate an Asset Index

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

Note: Division-period dummies included in factor analysis.

Appendix D: First Differences Robustness Check

If there are time-invariant household level fixed effects, the estimates found in Table 6 may be biased. Taking advantage of the panel characteristic of the survey data, we re-estimate with a fixed effects estimator. This method requires within-household variation in all the variables of interest, so re-analysis is necessarily restricted to that found in column 2, Table 6. The results are qualitatively the same as the pooled results: there are very few statistically significant relationships between the household characteristics examined here and idiosyncratic losses and those characteristics explain very little of the variation in idiosyncratic losses (Table D.1).

Table D.1. Fixed Effects Regression of Factors Contributing to Idiosyncratic Livestock Mortality

VARIABLES	Idiosyncratic Losses
Asset index#	0.0259
	(0.2165)
Asset index squared#	0.7102
	(0.6859)
HSNP participant	-0.0061
	(0.0128)
% herd camels&	0.0298
	(0.0367)
% herd cattle&	0.0243
	(0.0387)
Herd size (TLU/100)&	-0.0858
	(0.0948)
Herd size^2 (TLU^2/100^2)&	0.0151
	(0.1068)
Herd size^3 (TLU^3/100^3)&	-0.0124
	(0.0270)
Ratio income from livestock#	-0.0251*
	(0.0137)
Savings (KShs/1,000)#	0.0042**
	(0.0020)
Social groups count#	0.0015
	(0.0089)
Observations	5,124
Number of households	736
R-squared	0.011

Notes: Regression also includes a houseold size, dependency ratio, and a constant. #Variable is lagged by one period in order to reduce potential endogeneity. &Variable uses seasonal average monthly herd size. Cluster-robust standard errors in parenthesis. *** p<0.01, ** p<0.05, *p<0.1

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