How Basis Risk and Spatiotemporal Adverse Selection Influence Demand for Index Insurance: Evidence from Northern Kenya

Jensen, Nathaniel and Mude, Andrew and Barrett, Christopher

Cornell University, International Livestock Research Institute, Cornell University

11 July 2016

How Basis Risk and Spatiotemporal Adverse Selection Influence Demand for Index Insurance: Evidence from Northern Kenya

By Nathaniel D. Jensen, Andrew G. Mude and Christopher B. Barrett

June, 2016

Abstract: Basis risk – the remaining risk that an insured individual faces – is widely acknowledged as the Achilles Heel of index insurance, but to date there has been no direct study of its role in determining demand for index insurance. Further, spatiotemporal variation in risk, and therefore basis risk, creates the possibility of adverse selection. We use longitudinal household data to determine which factors effect demand for index based livestock insurance (IBLI). We find that both price and the non-price factors studied previously are indeed important, but that basis risk and spatiotemporal adverse selection play a major role in demand for IBLI.

JEL CODES: D81, O16, Q12

Jensen: Dyson School of Applied Economics and Management, Cornell University, 320J Warren Hall, Ithaca, NY, 14850 (e-mail: ndj6@cornell.edu); Mude: International Livestock Research Institute, Nairobi, Kenya (e-mail: A.MUDE@cgiar.org); Barrett: Dyson School of Applied Economics and Management, Cornell University, 301G Warren Hall, Ithaca, NY, 14850 (e-mail: cbb2@cornell.edu). This research uses data collected by a collaborative project of the International Livestock Research Institute, Cornell University, Syracuse University and the BASIS Research Program at the University of California at Davis. The authors wish to specifically thank Diba Galgallo, Munenobu Ikegami, Samuel Mburu, Oscar Naibei, Mohamed Shibia and Megan Sheahan for their remarkable efforts to collect useful and accurate data. Data collection was made possible, in part, by generous funding from the UK Department for International Development (DfID), the Australian Department of Foreign Affairs and Trade and the Agriculture and Rural Development Sector of the European Union through DfID accountable grant agreement No: 202619-101, DfID through FSD Trust Grant SWD/Weather/43/2009, the United States Agency for International Development grant No: EDH-A-00-06-0003-00, the World Bank's Trust Fund for Environmentally and Socially Sustainable Development Grant No: 7156906, and the CGIAR Research Programs on Climate Change, Agriculture and Food Security and Dryland Systems. The paper has also benefitted from comments on earlier drafts by attendees of the Development Microeconomics Seminar at Cornell University, and NEUDC 2014 in Boston University. This paper represents the views of its authors alone and not the positions of any supporting organizations. Any remaining errors are our sole responsibility.

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

Index insurance products have flourished over the past decade as a promising approach to address these obstacles. These products use easily observed, exogenous signals to provide insurance coverage for covariate risk. Anchoring indemnity payments to external indicators, not policyholders' realized losses, eliminates the need to verify claims, which is particularly costly in remote areas with poor infrastructure, and mitigates the familiar incentive challenges associated with moral hazard and adverse selection that plague traditional insurance. These gains do come at a cost, however; "basis risk" is the residual risk born by insurees due to the imperfect association between experienced losses and indemnification based on index values. Furthermore, a form of adverse selection may remain if prospective purchasers have information about expected indemnity payments that is not reflected in the product's pricing (Carriquiry & Osgood 2012; Jensen, Barrett, Mude 2016a). Such adverse selection could reflect inter-temporal information on upcoming conditions that affect insured covariate risk– such as climate forecasts – or knowledge that the effective loading (subsidy) rate varies across space.

The explosion of interest in index insurance has resulted in a proliferation of pilot programs across the developing world. A burgeoning literature addresses various aspects of theoretical and applied concerns in the design, implementation, and assessment of index insurance products (Barnett & Mahul 2007; Barrett *et al.*2007; Binswanger-Mkhize 2012; Chantarat *et al*. 2007; Clarke 2016; Miranda & Farrin 2012). Despite the celebrated promise of index insurance, uptake in pilot programs around the globe has been generally low, and there are as of yet no examples of clear success stories with demonstrable capacity for scalability or sustainability over the long run (Smith & Watts 2010; Hazell & Hess 2010; Leblois & Quiron 2013). As a result, most empirical research on index insurance in developing countries has focused on identifying the barriers to insurance uptake. The existing literature finds that demand for index insurance is price sensitive, as expected, but most studies find that demand is inelastic and between studies there is considerable variation in the price elasticity of demand, ranging from -0.44 to -1.16 (Mobarak & Rosenzweig 2012; Cole *et al*. 2013; Hill, Robles & Ceballos 2013). And, with the exception of the Ghanaian farmers studied by

Karlan *et al*. (2014), uptake has been low even at heavily subsidized prices.[1] With evidence that price plays only a small part in determining demand, researchers have turned to examining the role of household-specific non-price factors. Risk aversion, wealth, financial liquidity, understanding of the product, trust in the provider, and access to informal risk pooling commonly exhibit significant, although sometimes inconsistent, impacts on demand (Giné, Townsend & Vickery 2008; Chantarat, Mude & Barrett 2009; Pratt, Suarez & Hess 2010; Cai, de Janvry & Sadoulet 2011; Clarke 2016; Janzen, Carter & Ikegami 2012; Liu & Myers 2012; Mobarak & Rosenzweig 2012; Cole *et al*. 2013; McIntosh, Sarris, & Papadopoulos 2013; Dercon *et al*. 2014).

Although basis risk and the possibility of spatiotemporal adverse selection are widely understood as prospective weaknesses of index insurance, the empirical research has thus far not directly explored the role that either of these product-specific factors plays in influencing product uptake. But if the insurance index is imperfectly correlated with the stochastic welfare variable of interest (e.g., income, assets), then index insurance may offer limited risk management value; indeed purchasing index insurance can increase, rather than decrease, purchasers' risk exposure (Jensen, Barret & Mude 2016a). Furthermore, prospective purchasers may perceive that an index insurance product is mispriced for their specific location or for the upcoming season, given information they have on the average and period-specific covariate risk in a location.

Both of these problems exist generally in index insurance contracts and either might adversely affect uptake. Yet the impact of these prospective weaknesses in index insurance products has not been carefully researched to date, although a few studies use coarse proxies for idiosyncratic risk—a component of basis risk—those studies rely on hypothetical and untested relationships between the proxies and basis risk (Karlan *et al*. 2014; Mobarak & Rosenzweig 2012). To the authors' knowledge, no study to date, examines the role of spatiotemporal adverse selection. This lacuna arises primarily because the vast majority of products fielded to date remain unable to determine the level of basis risk inherent in their product design; the products were designed from data series on index variables (e.g., rainfall, crop growth model predictions), not from longitudinal household asset or income data from the target population to be insured.

This paper fills that important gap, exploiting an unusually rich longitudinal dataset from northern Kenya and a research design that includes randomized inducements to purchase index-based livestock insurance (IBLI) and a randomized IBLI education intervention that improves understanding of IBIL, in order to examine the relationship between basis risk and spatiotemporal adverse selection on index insurance uptake. This is the first paper to do so using observed data on losses to examine the role of basis risk in demand for

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

index insurance a low-income country context. In addition, specific features of the contracts and data allow us to examine the role of adverse selection in demand, as topic wholly unstudied with respect to index insurance because it is often assumed to be non-existent or negligible.

Echoing the prior literature, we find that price, liquidity, and social connectedness affect demand in the expected ways. In addition, we find that increased basis risk is associated with lower demand and that households' response to basis risk is stronger among those with experimentally increased knowledge of IBLI. Although we argue and provide evidence that basis risk is almost surly exogenous, we cannot vary it experimentally and so, make no causal claims.

Furthermore, we observe patterns in demand that are consistent with spatiotemporal adverse. Households in divisions with greater average losses (insurable risk) and those with less basis risk have greater demand for index insurance. Again, the response to basis risk is stronger among those that have a better understanding of the product. There is also strong evidence of intertemporal adverse selection as households are more likely to purchase insurance and purchase greater coverage before seasons in which remotely sensed data indicate coming covariate threats, which has large implications for the profits of the underwriters. Additional analysis of the relationship between subjective expectation of coming rangeland conditions and demand shows that households are also responding to private information on conditions, but in this case they reduce demand during seasons in which they expect poor rangeland conditions. One plausible interpretation of the above findings on intertemporal adverse selection is that demand increases in response to signals of coming covariate shocks and falls in response to the threat of idiosyncratic shocks.

These findings suggest that product design is extremely important to get right and that, although it is expensive to do so, it is important to collect household level socio-economic, index insurance demand, and loss data and to use the data to improve product qualtiy. This and other research on IBLI has led to multiple iterations of the IBLI product as the implementers strive to create a high quality product that generates considerable demand. To date, many of those changes have been successful, generating considerable demand as the IBLI product was introduced into other regions of Kenya and Ethiopia.

The remainder of the paper is organized as follows. Section 1 discusses risk among pastoralists in northern Kenya and the motivation for and design of the IBLI product offered to them. Section 2 develops a stylized model of livestock ownership and the role of insurance, which is then developed into four hypothesis on the structural determinants of demand. Section 3 presents the research design and data, followed by an explanation and summary of key variables in Section 4. Section 5 describes the econometric strategy used to analyze demand for IBLI. The hypotheses are tested in Section 6, which then closes with a discussion of the implications of our findings.

1 Drought-Related Livestock Mortality & Index Insurance in Kenya

Livestock represent the principal source of income across most pastoral households (mean=69% and median=95% in our data) as well as the highest value productive asset they own. Livestock face considerable mortality risk, rendering pastoral households particularly vulnerable to herd mortality shocks. Among these, drought-related livestock mortality has consistently emerged as the greatest risk faced by pastoralists in the arid and semi-arid lands (ASAL) of the Horn of Africa (McPeak & Barrett 2001; McPeak, Little & Doss 2012, Barrett & Santos 2014). For example, between June 2000 and June 2002, surveyed pastoralists reported that drought-related factors accounted for 53% of the livestock deaths that they experienced, and disease, which is often associated with droughts, caused an additional 30% mortality during that period (McPeak, Little & Doss 2012). Drought is the reported cause of 62% of livestock mortality in our 2009-12 sample from northern Kenya. Droughts represent a covariate risk that may be especially difficult for existing social risk pooling schemes to handle because losses can impact all members of the risk pool. Thus, the seemingly largely covariate risk profile pastoralists face seems well-suited for coverage by an index product.

The index based livestock insurance (IBLI) product was launched as a commercial pilot in January 2010 in the arid and semi-arid Marsabit District of Kenya to offer formal insurance coverage against livestock losses due to drought. Specifically, the IBLI product covers predicted area average livestock mortality that arises due to severe forage shortages associated with drought.

The IBLI index is derived from the Normalized Difference Vegetation Index (NDVI), an indicator of photosynthetic activity in observed vegetation as reflected in spectral data remotely sensed from satellite platforms at high spatiotemporal resolution. These NDVI data are reliably and cheaply accessible in near real-time, and with a sufficiently long historical record to allow for accurate pricing of the IBLI product. The statistical relationship between NDVI and livestock mortality was estimated using historic household level livestock mortality rates and NDVI values from January 2000 through January 2008 and then tested out-of-sample against a different set of seasonal household panel data collected 2000-2 in the same region (Chantarat *et al*. 2013).[2] The resulting response function generates estimates of division average livestock

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

mortality rate.[3] IBLI appears to be the only index insurance product currently on the market that was developed using longitudinal household data so as to minimize the design component of basis risk.[4]

A commercial underwriter offers IBLI contracts written on this predicted livestock mortality rate index (see Chantarat *et al*. 2013 for more details on data and product design). The index is calculated separately for each of the five administrative divisions in Marsabit, allowing for variation in indemnity rates between divisions. The commercial underwriter set a single strike level—the index level above which indemnity payments are made—at 15% predicted livestock mortality and aggregated the five index divisions into two premium regions. Notably, the aggregation of index divisions into premium regions results in variation in loadings/subsidies between index divisions, opening the door for spatial adverse selection.[5] A detailed summary of the contract parameters (e.g., geographical segmentation of coverage, temporal coverage of the contract, conditions for contract activation, indemnification schedule, pricing structure) is presented in Appendix A.

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

Notably, there was a fall in IBLI uptake over the 2010-2012 period. Although inconsistency of sales windows, a change in the commercial insurance provider, and variation in extension and sales protocols may have depressed sales, heterogeneity in demand suggests that other factors also influenced purchases. Tracking household purchase patterns across seasons shows considerable variation in when households make their first purchase, if they continue to purchase, or if they allow their contract to lapse (Table 2). Such behavior suggests dynamic factors play a significant role in insurance demand. In the next section, we offer a simple model of index insurance demand and examine the role that basis risk and spatiotemporal adverse selection could play in determining demand.

---

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

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

[5] The aggregation of index divisions into premium regions had been dropped in the newer IBLI products introduced in 2013.

2 Demand for Index Based Livestock Insurance

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

Let households maximize their expected utility, which is an increasing and concave von Neumann-Morgenstern function that satisfies U'>0, U''<0. Utility is defined over wealth, measured as end-of-period herd size expressed in tropical livestock units (TLU).[6] Households have an initial livestock endowment, TLU_0, but their herds are subject to stochastic losses at rate L. Households have the option of purchasing livestock insurance at the rate of p per TLU insured, where $p \in [0,1]$.[7] Coverage is then the fraction of the initial herd insured ($\widetilde{tlu}$). The insurance makes indemnity payments according to an index, which is the predicted rate of index-division average livestock losses ($I \in [0,1]$).[8] The utility maximization problem and budget constraint can be described as follows, where E is the expectation operator;

(1)
$$\max_{\widetilde{tlu}} E[U(TLU)]$$
$$subject\ to: TLU = TLU_0 - L * TLU_0 - \widetilde{tlu} * TLU_0 * p + \widetilde{tlu} * TLU_0 * I$$

Substituting the budget constraint into the utility function and using a second order Taylor expansion allows the expected utility maximization problem to be approximated as a function of original livestock endowment and adjustments to herd size associated with losses, premium payments and indemnity payments.[9] To simplify notation we use $U = U(TLU_0)$, $U' = \frac{\partial U(TLU_0)}{\partial TLU_0}$, and $U'' = \frac{\partial^2 U(TLU_0)}{\partial {TLU_0}^2}$. The necessary first order condition becomes

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

---

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

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

8 The index-division refers to the geographic region defined by the insurance product for which a single index determines indemnity payments.

9 $\max_{\widetilde{tlu}} E\left[U(TLU_0) + U'(TLU_0) * \left(TLU_0(- * L - \widetilde{tlu} * p + \widetilde{tlu} * I)\right) + \frac{1}{2}U''(TLU_0)\left(TLU_0(-L - \widetilde{tlu} * p + \widetilde{tlu} * I)\right)^2\right]$

The first order condition can be solved for optimal insurance purchases. We use the representations $E[x] = \bar{x}$, $Cov(x, y) =$ the covariance of x and y, and $Var(x)$ = variance of x, where x and y are representative variables.

With some algebra, the optimal proportion of original herd to insure can be written as equation (3).

(3)
$$\widetilde{tlu}^* = \frac{TLU_0 * U'' * [\bar{L} * (\bar{I} - p) + Cov(I, L)] - U' * (\bar{I} - p)}{TLU_0 * U'' * \left((\bar{I} - p)^2 + Var(I)\right)}$$

The covariance term captures the role of basis risk. If there is no basis risk ($cov(I, L) = Var(I)$) and premiums are actuarially fairly priced ($\bar{I} = p$), full coverage is optimal ($\widetilde{tlu}^* = 1$). Relaxing the premium constraint ($\bar{I} \neq p$), optimal coverage is not monotonic in premium rates because changes to premium rates not only effect the opportunity cost of premium payments, but also have wealth effects that are ambiguous in their impact on demand.[10] Clarke (2016) discusses a similar outcome.

If the basis risk constraint is also relaxed, $cov(I, L) \neq Var(I)$ and Equation (3) can be rewritten to explicitly include the variance of the difference between the index and individual losses ($Var(L - I)$), a definition of basis risk.[11]

(3')
$$\widetilde{tlu}^* = \frac{TLU_0 * U'' * \left[\bar{L} * (\bar{I} - p) + {}^1\!/_2 * [Var(L) + Var(I) - BasisRisk]\right] - U' * (\bar{I} - p)}{TLU_0 * U'' * \left((\bar{I} - p)^2 + Var(I)\right)}$$

As the basis risk increases, optimal coverage falls ($\frac{d\,\widetilde{tlu}^*}{dBasisRisk} = -\frac{1}{2[(\bar{I} - p)^2 + Var(I)]} < 0$). In addition, the reduction in optimal coverage due to basis risk is exacerbated by increasing prices ($\frac{\partial^2\,\widetilde{tlu}^*}{\partial p \partial BasisRisk} = -\frac{(\bar{I} - p)}{[(\bar{I} - p)^2 + Var(I)]^2} < 0$) when premiums are below the actuarially fair rate ($\bar{I} - p > 0$), while demand sensitivity to basis risk falls with premiums when premiums are above their actuarially fair rate (($\bar{I} - p < 0$)). Intuitively, demand is most sensitive to basis risk when premiums are near their actuarially fair rate and becomes less sensitive to basis risk as premiums are increasingly subsidized or loaded. These two findings lead to our first core set of hypothesis.

Hypothesis 1: Demand falls as basis risk increases and the sensitivity of demand to basis risk increases as premiums approach the actuarially fair rate.

---

[10] $\frac{\partial \widetilde{tlu}^*}{\partial(\bar{I} - p)} = \frac{TLU_0 * U'' * \bar{L} - U'}{TLU_0 * U'' * \left((\bar{I} - p)^2 + Var(I)\right)} - \frac{2 * TLU_0 * U'' * \delta * \{TLU_0 * U'' * [\bar{L} * (\bar{I} - p) + Cov(I, L)] - U' * (\bar{I} - p)\}}{\left[TLU_0 * U'' * \left((\bar{I} - p)^2 + Var(I)\right)\right]^2}$

[11] Basis Risk $= Var(L - I) = Var(L) + Var(I) - 2Cov(L, I)$, so that $Cov(L, I) = {}^1\!/_2\,(Var(L) + Var(I) - Basis\ Risk)$

2.1 Product Understanding

In some cases it may be that households do not understand the insurance product well. For example, a household might think that the insurance product indemnifies all losses or that indemnity payments are always made at the end of every season. In either of the afore mentioned cases, basis risk should play no role in the purchase decision, although it could have a large impact on the eventual welfare outcomes of the purchase decision. In actuality, there are likely to be households that partially understand the insurance contract but have a variety of misconceptions.

Let an individual's understanding of the product be summarized by the term $I_i = I + z_i$, where I continues to indicate the index that determines indemnity payments, $z_i$reflects the individual's misinformation and I_i is the index required to produce the indemnity payment that the individual expects to receive. The individual believe that the index covaries with losses by $Cov(I_i, L)$, while it actually covaries by $Cov(I, L)$. The difference between the two is $Cov(z_i, L)$. The optimal purchase is $\widetilde{tlu}^* = \frac{TLU_0 * U'' * \left[\bar{L} * (\bar{I} - p) + {}^{1}/_{2} * [Var(L) + Var(I) - BasisRisk] + Cov(z_i, L)\right] - U' * (\bar{I} - p)}{TLU_0 * U'' * \left((\bar{I} - p)^2 + Var(I) + Var(z_i) + 2 * Cov(I, z_i)\right)}$. Intuitively, when the factor $Cov(z_i, L)$>0, the client overestimates the accuracy of the index and increases purchases $\left(\frac{d\,\widetilde{tlu}^*}{dCov(z_i, L)} = \frac{1}{(\bar{I} - p)^2 + Var(I) + Var(z_i) + 2 * Cov(I, z_i)} > 0, \forall\ Cov(I, z_i) > 0\right)$.

Misconceptions about the product express themselves as error in the household's internal estimates of basis risk and thus value proposition of the product. The error could be in the direction of reduced or increased basis risk, but works towards moderating the relationship between basis risk and demand. This relationship leads to our next hypothesis:

Hypothesis 2: As households' knowledge of the product improves, they will become more responsive to actual basis risk.

2.2 Spatiotemporal Adverse Selection

Indemnifying covariate losses, rather than individual losses, eliminates the prospective impact on insurer profits of within index-division cross-sectional adverse selection by decoupling indemnity payments from individual losses.[12] But group-level adverse selection can reemerge if households have information on the likelihood of an indemnity payment in the coming season that is not reflected in the premium. For example,

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

ecological conditions during the sales window may have predictive power as to the likelihood of an upcoming drought. In this case, the consumer has a signal (observed ecological conditions) that provides information on the probability distribution of coming average losses and thus the likelihood of indemnity payments. If that information is not incorporated in the product's pricing, then we expect demand to respond to the increase in risk. Even in cases when the insurer can observe the same information that households can, contracts are not always written with variable premium rates. Rather, insurers and reinsurers often set prices according to historic averages and are commonly reluctant to change premiums season by season.

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

(3'')
$$\widetilde{tlu} = \frac{TLU_0 U''[(\bar{L} + y^*)(\bar{I} + x^* - p) + cov(I, L)] - U'(\bar{I} + x^* - p\,)}{\left[TLU_0 U''\left((\bar{I} + x^* - p)^2 + Var(I)\right)\right]}$$

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

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

By contrast, if the signal pertains only to the expected index, the outcome is similar to changes in loadings/subsidies and is not monotonically increasing or decreasing in x^*.[13] As with the effect of premium rates on demand, the impact of signals that inform on both losses and index levels is an empirical question.

13 $\frac{\partial \widetilde{tlu}^*}{\partial x^*} = \frac{\{TLU_0 U'' \bar{L} - U'\}}{TLU_0 U''\left((\bar{I} + x^* - p)^2 + Var(I)\right)} - \frac{2(\bar{I} + x^* - p) TLU_0 U'' \{TLU_0 U''[(\bar{L} + y^*)(\bar{I} + x^* - p) + cov(I,L)] - U'(\bar{I} + x^* - p\,)\}}{\left[TLU_0 U''\left((\bar{I} + x^* - p)^2 + Var(I)\right)\right]^2}$

If those signals correctly predict coming conditions, such behavior will be evident in a temporal correlation between demand and index value.

A related, spatially defined form of group-level adverse selection can occur when there is variation in the difference between the expected index value and the premium rates or in the index performance between distinct geographic regions.[14] Differences between expected indemnity and premium rate are likely to be common for products with little data with which to estimate the expected indemnity payment. Such variation represents, in essence, variations in the subsidy/loading rates between divisions caused by error in the provider's estimated expected index values or perhaps intentionally (e.g., variation in state subsidy rates). This type of spatial adverse selection is covered in the above examination of the effects of varying the subsidy/loadings.

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

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

This simple, static model conforms to our expectations of reduced demand with increased basis risk. It predicts that basis risk reduces demand but that it will be less important for those who face extremely high or low premium and for those that do not understand the product well. In addition, the model is easily extended to include factors that may contribute to spatiotemporal adverse selection. It predicts that we should expect to see variation in demand within divisions over time that is correlated with rangeland conditions during the sales windows and among divisions based on spatial average differences in risk and basis risk. The important point of the model and these analytic findings is that the design features of an index insurance product may significantly attenuate demand irrespective of the household characteristics extensively studied in the literature to date.

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

3 Research Design & Data

Before any public awareness campaign began surrounding the January 2010 launch of the IBLI pilot, the IBLI research team began to implement a comprehensive household survey that annually tracks key parameters of interest such as herd dynamics, incomes, assets, market and credit access, risk experience and behavior, demographics, health and educational outcomes, and more. The initial baseline survey was conducted in October of 2009, with households revisited annually thereafter in the same October-November period. A total of 924 households were sampled across 16 sub-locations in four divisions (Central, Laisamis, Loiyangalani and Maikona) of Marsabit District, selected to represent a broad variation of livestock production systems, agro-ecology, market accessibility and ethnic composition.[15] The codebook and data are publically available at http://livestockinsurance.wordpress.com/publications/.

A few key elements of the survey design are important to note. Two randomized encouragement treatments were implemented to help identify and test key program parameters on demand. In the first, a sub-sample was selected to play an educational game based on the pastoral production system and focused on how IBLI functions in the face of idiosyncratic and covariate shocks. The game was played in nine of the 16 sites among a random selection of half of the sample households in each selected site, and took place just before the launch of sales in January 2010 (McPeak, Chantarat & Mude 2010).

The second encouragement treatment involved a price incentive that introduced exogenous variation in premium rates. Discount coupons were randomly distributed to about 60% of the sample before each sales season. The coupons were evenly distributed among 10%, 20%, 30%, 40%, 50% and 60% discount levels. Upon presentation to insurance sales agents, the coupon entitled the household to the relevant discount on premiums for the first 15 TLU insured during that marketing season.[16] The coupons expired after the sales period immediately following their distribution. Each sales period has a new randomization of discount coupons.

The IBLI team also coordinated survey sites to overlap with the Hunger Safety Net Program (HSNP), a new cash transfer program launched by the Government of Kenya in April 2009 that provides regular monthly cash transfers to a select group of target households in the northern Kenya ASAL (Hurrell & Sabates-Wheeler 2013). The regularity and certainty of this cash transfer may impact household liquidity constraints and therefore demand for IBLI. Site selection for IBLI extension encouragement was stratified to include both communities targeted by HSNP and other, nearby communities that were not. Figure 1

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

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

displays the project's sample sub-locations across Marsabit and illustrates how they vary in terms of the noted elements of the study design. Discount coupons were randomly distributed without stratification.

This paper uses data from four annual survey rounds from between 2009 to 2012. The attrition rate during this period was less than 4% in each round. An analysis of attrition is found in Appendix B. There are a number of small but statistically significant differences between those households who remained in the survey and those who left the survey (Table B4), as well as between those who exited the survey and their replacements (Table B5). For a discussion of the causes of attrition see ILRI (2012). We control for these characteristics in our analysis to mitigate prospective attrition bias introduced by this possible selection process, but the rate of exit is low enough and differences small enough that attrition should be of little worry.

It is important to note that analysis of demand is performed seasonally while the survey data were collected annually. Although seasonal data were collected for many variables through recall, some characteristics were collected for only one reference point annually. In those cases, the annual values collected in October/November are used to represent household characteristics during the previous March-September LRLD insurance season and the current October-February SRSD season. When estimating within household average characturistics, all eight seasonal observations are used to estimate a single statistic, which is then treated as a constant over all periods. These details are described in more detail in the following section and in Appendix B.

4 Discussion of Key Variables

IBLI purchases among those surveyed and within the general population across the Marsabit region were greatest in the first sales window and declined in the following periods (Table 1).[17] About 45% of the balanced panel (N=832) purchased IBLI coverage at least once during the four sales periods covered in these data, a relatively high rate of uptake when compared against other index insurance pilots in the developing world. Of the 576 purchases observed, the average coverage purchase was for 3.21 TLUs or 24% of the average herd size in our sample during the sales windows. Table 2 details the frequencies of observed transitions between purchased coverage, existing coverage, and lapsed coverage. Figure 2 illustrates the proportion of the sample that purchased IBLI during each sales window and the level of purchase, conditional on purchasing.

Although existing research, which we discuss in detail below, has already provided a framework by which to understand many of the household-level factors the influence index insurance demand, we are in

---

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

the unique position to empirically examine the role of basis risk and spatiotemporal adverse selection. Both are thought to impact demand but have not yet been tested using observations of household losses. At the same time, we reinforce previous findings in the literature by including factors that have been found to influence demand elsewhere. This section discusses the key variables used in the analysis.

4.1 Basis Risk

Our first and second hypothesis state that household demand will respond to basis risk. But, households are unlikely to have information about the accuracy (or inaccuracy) of an index product before the product has been introduced. In cases where index products are new, such as in the Marsabit IBLI pilot we study, individuals must learn about basis risk as index performance is revealed through observations of published index values (Karlan *et al*. 2014).

To construct our variable of basis risk, we assume that households must learn about it by observing it. In addition, we assume that overpayments represent a positive event from the household's perspective, so that our definition of basis risk is a measure of underpayments. We then construct a simple measure of the average squared observed underpayments. We assume households expect no basis risk in the first sales round. After the first round, households discard their initial naive expectation and update so that their posterior is the average squared observed basis error. They continue to do so in each of the following rounds.

$$Basis\ Risk_{lit} = \frac{1}{t-1}\sum_{s=1}^{t-1} max(L_{lis} - I_{lt}, 0)^2 \qquad (4)$$

Table 3 presents summary statistics for the observed basis risk estimates as well as the seasons used to make each estimate.

There is a risk that observed basis risk is endogenous to our variables of interest. One key concern is moral hazard, that households may make riskier herding decisions in this case, in response to insurance coverage, leading them to have higher observed basis risk in subsequent rounds. We test for moral hazard in what amounts to a difference-in-differences analysis testing for the effect of treatment—purchasing insurance—on livestock morality rates. We find that current period IBLI purchases have no effect on current period livestock mortality rates (Coef.=-0.02, St. Err.=0.037, analysis not included).[18]

---

[18] We should note that Jensen, Barrett, and Mude (2016) use an instrumental variable process to find that the cumulative impact of past and current IBLI coverage has a negative causal effect on livestock losses by the final survey round in 2012, but they also found that households reduce herd-

There is also a risk that the index quality is correlated with regional factors that are unobserved by the econometrician and the effect demand; access to banks for example. Here it becomes useful to decompose basis risk into its design and idiosyncratic components.[19] Design risk arises due to differences between predicted and actual division-average livestock mortality and can be corrected by adjusting the index. One might think of design risk as an indicator of contract adherence, so far as it is the result of a deviation between the intended and actual coverage provided by a policy. If there are unobserved characteristics shared by households within a division that result in systematically higher or lower design error and that effect demand, design error is endogenous to our variables of interest. Regressing observed design error onto division dummy variables shows that there are no such time-invariant characteristics (analysis not included). Thus, we assume that observed design error is largely exogenous in our analysis.

The second component of basis risk—idiosyncratic risk—is due to differences between the covariate and individual losses and is intrinsically uncorrectable in the index. Figure 3 displays histograms of the estimated correlation between individual losses and covariate losses in each division. There is clearly a great deal of variation within and between divisions in the individual-covariate loss correlation. Indeed, 13.3% of households have a non-positive correlation, implying that even if IBLI suffered from zero design risk, it would be risk-increasing for them despite its insurance label. Although it is reasonable to be cautious about the exogeneity of idiosyncratic risk, other work has shown that it mostly random—unexplained by community fixed effects, household fixed effects, or a large list of more than 15 socioeconomic household characteristics (Jensen, Barrett & Mude 2016a).

Thus, our basis risk variable can be thought of as the aggregate of observed differences between the household's losses and covariate losses and the difference between covariate losses and the index. The first appears to be nearly random while the later does not vary systematically between divisions.

4.2 Spatiotemporal Adverse Selection

IBLI is susceptible to intertemporal adverse selection because droughts leading to high livestock mortality are often the result of multiple seasons with poor precipitation so that households may rationally avoid purchasing insurance if conditions are good at the time of purchase. In addition, pastoralists may have signals (e.g., radio, indigenous forecasting methods, mobile applications) that inform them on the coming season's precipitation or weather. We include two variables—*Pre-Czndvi* and the household's reported

size through livestock sales so that there is no impact on mortality rates. The analysis here finds that there is no connection between current purchases and current mortality rates.

[19] We did not distinguish between design and idiosyncratic risk in Section 2 because their combined effect determines the level of risk that an insured individual retains.

expectation of rangeland conditions in the coming season—to capture ecological conditions that pastoralists may take into consideration while making their purchase decision, which could lead to intertemporal adverse selection.

Pre-Czndvi is a variable used in the IBLI response function to increase the accuracy of the index by controling for conditions at the beginning of the season. It is calculated by summing standardized NDVI values from the beginning of the previous rainy season until the current sales period. Higher *Pre-Czndvi* values indicate greater relative greenness during the rainy season leading up to the current insurance season. Although the index takes *Pre-Czndvi* into account when estimating livestock mortality, and premiums could be adjusted to reflect the level of risk at the beginning of a season, the insurer and reinsurer have chosen not to vary premium rates to account for this observed intertemporal variation in livestock mortality risk. *Pre-Czndvi* has a statistically significant and negative relationship with predicted livestock mortality rates (column 1, Table 4). Thus, if households observe the relative greenness that is captured by *Pre-Czndvi*, they could use those observations to help predict coming index values and adjust their purchase decisions accordingly.

A set of dummy variables specify the household's stated expectations for the coming season's rangeland conditions: good, normal, or bad. Expectation of good (bad) rangeland conditions are negatively (positively) and statistically significantly correlated with end-of-season index values (predicted livestock mortality rates) as is expected if they correctly predicted coming rangeland conditions (column 2, Table 4). Hypothesis 3 states that as long as premium rates are below the expected indemnity rate, which they are, households expecting higher livestock mortality rates will increase purchases but is ambiguous about the impact of that expectation if it also suggests higher index values.[20]

Households' expectations of rangeland conditions may contain the same information that is captured by the *Pre-Czndvi* variable or households may be observing additional information that is not captured by the remotely sensed NDVI. Regressing predicted livestock mortality onto both *Pre-Czndvi* and households' expectations of coming conditions provides strong evidence that the households have additional information that is not captured by *Pre-Czndvi*. The implication is the although IBLI providers could reduce the potential for intertemporal adverse selection associated with initial rangeland conditions by adjusting premium rates according to *Pre-Czndvi,* they would continue to face risk of intertemporal adverse selection arising from accurate private information held by their potential consumers. According to Hypothesis 3, increases in *Pre-Czndvi* and the expectation of good rangeland conditions should be associated with reduced demand for IBLI.

---

[20] The effective seasonal subsidies beyond actuarially fair rate (E[indemnity payment rate]-seasonal premium rate) for the periods examined were are as follows: Central/Gadamoji 0.0249, Laisamis 0.0171, Loiyangalgani 0.0148, and Maikona 0.017

We also test for spatially defined adverse selection, which could emerge due to variation in the subsidy/loading rate in policies or from variation in division average quality of the policies. Variation in subsidy/loading rate results from the aggregation of index divisions into larger premium regions so that lower risk divisions are implicitly subsidizing the premium rates of higher risk division in the same premium region. Division-average livestock mortality rate is used to capture division-level differences in risk, and thus actuarially fair premium rates of a perfect index product. Division average observed levels of basis risk are used to test for the effects of variation in product quality. According to Hypothesis 4, we expect demand for IBLI to increase with division average livestock mortality rates and to decrease with basis risk.

4.3 Additional Key Variables

Within the standard model of insurance, exposure to risk coupled with risk aversion is the fundamental reason for insurance demand. At any level of positive exposure to risk, the benefits of indemnified losses increase with level of risk aversion. But the impact of risk aversion on demand is somewhat ambiguous when market imperfections, such as basis risk or premium loadings, are present. Most empirical studies of index insurance demand assume a monotonic relationship between risk aversion and demand, often finding that increased risk aversion is associated with decreased demand (i.e., Giné, Townsend & Vickery 2008; Cole *et al*. 2013). This negative correlation between risk aversion and demand for insurance has been interpreted as evidence that demand for index insurance in developing countries is more similar to technology experimentation/adoption than to neoclassical models of insurance demand. Hill, Robles, and Ceballos (2013) allow for a nonlinear relationship, specifically testing for hump-shaped demand across risk aversion as predicted by Clarke (2016), but find no significant difference in demand across the domain of observed risk aversion. In a setup similar to that used by Hill, Robles, and Ceballos (2013), we allow for a non-linear relationship between risk aversion and demand as predicted by (Clarke 2016).

Whether households place more importance on absolute or relative risk is an empirical question that has not yet been addressed in the context of index insurance. To determine which is more important, we include total herd size and ratio of income generated from livestock and livestock related activities. Total herd size provides an absolute measure of exposure to asset risk associated with IBLI insurable assets, while the ratio of income that is generated from livestock and livestock related activities approximates the relative income risk associated with livestock mortality. We also include the variance of a household's livestock mortality rate during the three seasons before IBLI was introduced as an exogenous control for historic risk.

Theory and empirical evidence are also ambiguous as to how wealth should affect demand for insurance when prices are actuarially unfavorable. Clarke (2016) shows that the relationship between wealth and demand is not monotonic for most reasonable utility functions in such environments. Empirical studies offer contradictory evidence, finding that demand increases (Cole *et al*. 2013; Mobarak & Rosenzweig 2012) or decreases (McIntosh, Sarris, & Papadopoulos 2013) with variables associated with wealth. The empirical literature on poverty traps, which have been shown to exist among east African pastoralists (Lybbert *et al*. 2004, Barrett *et al*. 2006, Santos and Barrett 2011), indicates that demand may be non-linear in wealth, changing dramatically across certain asset thresholds as households try to avoid or to break free of a low asset dynamic equilibrium (Chantarat *et al*. 2014; Janzen, Carter & Ikegami 2012; Lybbert, Just, & Barrett 2013). We summarize household wealth with an asset index generated through factor analysis of an extensive list of household construction materials, productive assets excluding livestock, and other durables (Appendix B).

Lack of liquidity is often found to constrain demand. Mobarak and Rosenzweig (2012) found that lack of cash was the primary reason given by Indian farmers for not purchasing an available index insurance product. Although liquidity is likely correlated with wealth, it can constrain demand at any wealth level (Cole *et al*. 2013). In order to capture liquidity, we calculate the sum of cash savings on hand or placed within any of several formal and informal savings arrangements. A household's savings are liquid and provide a lower bound estimate of access to liquid capital. We also include an estimate of monthly income and participation in the Hunger Safety Net Program (HSNP), an unconditional cash transfer program that was launched in the Marsabit region in 2009. [21] Although HSNP participation was not random within communities, we are able to partially identify the impact of transfers on demand by controlling for the known and corroborated household selection criteria, which are continuous variables with exogenous cutoffs, and HSNP community selection.[22]

Understanding the IBLI contract is critical for informed demand. Although the IBLI survey does include a simple test of accuracy of IBLI knowledge, that evaluation could not be collected before the first sales period and is likely endogenous to the decision to purchase an IBLI policy.

As a proxy for IBLI knowledge, we include a dummy for participation in the randomized education game described in the research design section. Balance tables are found in Appendix C. Participation in the game had a strongly positive and significant impact on performance on the IBLI knowledge test (Table 5). There is some prospect that game participation leads to purchasing through a mechanism other than knowledge (e.g., trust, a sense of obligation) so that the above test reported in Table 5 captures an increase in knowledge

---

[21] HSNP provides transfers every two months to eligible households for at least two years. The bimonthly transfers started at 2,150Ksh in 2009 (about USD25) and increased to 3,000Ksh in 2011 and then increased again in 2012 to 3,500Ksh in order to help households cope with a severe drought. 3,500Ksh could have purchased insurance for about 7 cattle in the lower Marsabit region at that time. There was no retargeting of or graduation from HSNP, which could have led to perverse incentives not to purchase IBLI if insurance has a beneficial impact on wealth.

[22] For more details on the HSNP program logistics go to http://www.hsnp.or.ke/ while analysis of impacts can be found in Hurrell & Sabates-Wheeler (2013) and Jensen, Barrett and Mude (2016b).

due to purchase rather than due to the educational component of the game. This is tested by restricting the analysis to only those households who never purchase IBLI. As reflected in the second row of Table 5, among those who never purchase IBLI, participation in the game increased average IBLI knowledge test scores by over 21% (p-value<0.001), providing strong evidence that randomized participation in the extension game directly leads to greater IBLI knowledge.

Access to informal insurance schemes can be an important factor in demand for formal insurance. Mobarak and Rosenzweig (2012) show that informal risk pools that insure against idiosyncratic shocks complement index insurance with basis risk while informal schemes that protect against covariate shocks act as a substitute. In the pastoral societies of east Africa, informal risk sharing through livestock transfers and informal credit appears to be modest at best (Lybbert *et al*. 2004; Santos & Barrett 2011) and not timed so as to reduce the impact of shocks or to protect assets (McPeak 2006). But, because informal risk sharing is extremely relevant to this work and has empirically been found to impact demand for index insurance in India (Mobarak & Rosenzweig 2012), we include the number of informal groups that the household participates in as a coarse indicator of potential access to risk pooling.[23]

Price surely matters to insurance uptake (Cole *et al*. 2013, Giné, Townsend & Vickery 2008, Karlan *et al*. 2014). The effective premium rate is calculated as the natural log of the premium rate after accounting for randomly distributed discount coupons.

Appendix B describes how each variable is constructed and which are lagged to avoid capturing changes due to paying the premium or due to behavior responses to having IBLI coverage. Table B2 provides summary statistics, distinguishing between those households who never purchased IBLI over the four sales windows and those who purchased at least once. Differences in unconditional means between the two groups show that the groups are mostly similar except for in those variables directly associated with purchases.

5 Econometric strategy

We seek to identify the factors that influence demand for IBLI. Insurance demand is best modeled as a two stage selection process. Propensity to purchase is first determined as the household decides whether or not to buy IBLI. Those households who choose to purchase then decide how much to buy. Let h_{it}^* and y_{it}^* be latent variables that describe the categorical desire to purchase insurance and the continuous, optimal level of purchase, respectively. If $h_{it}^* > 0$ we observe the positive level of purchase $y_{it} = y_{it}^*$, and if $h_{it}^* \leq 0$, we observe $y_{it} = 0$. We write the process as a function of time invariant individual characteristics (c_i, d_i)

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

including a constant term, time varying individual and division characteristics (x_{it}, z_{it}), and error terms (u_{it}, v_{it}) as follows.

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

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

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

Accounting for unobserved household level fixed effects is then a matter of applying panel data estimation methods to Heckman's framework. For short panels, the standard fixed effects approaches suffer from the incidental parameters problem when applied to probit models.[24] But, if the data generating process is best described by the fixed effects model, pooled and random effects models will also be biased. Greene

---

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

(2004) compares the magnitude of the bias introduced by estimating pooled, random effects, and fixed effects probit parameters for data generated by a probit process with fixed effects. At T=3 and T=5, Greene finds the random effects estimates are the most biased, and that the bias associated with the pooled and fixed effects models are similar in magnitude. In addition, standard errors are likely to be underestimated in the fixed effect model.

For our primary analysis, we use a variation of pooled estimates developed by Wooldridge (1995), which builds off of earlier work by Mundlak (1978) and Chamberlain (1980), to allow for within household time invariant factors, but assumes that those factors are reflected in observed within-household mean characteristics ($\bar{x}_i^{FE}$) and assumes independence conditional on those means. In addition the errors are assumed to be distributed normally.

(6)

$$c_i = \bar{x}_i^{FE'}\gamma_1 + e_{it}^c\,,\; e_{it}^c|\bar{x}_i^{FE} \sim N(0,\sigma_e^2)$$

$$d_i = \bar{x}_i^{FE\prime}\delta_1 + e_{it}^d\,,\; e_{it}^d|\bar{x}_i^{FE} \sim N(0,\sigma_e^2)$$

$$\bar{x}_i^{FE} = \frac{1}{T}\sum_T x_{it}^{FE}\,,\; x_{it}^{FE} \subseteq x_{it}, z_{it}$$

As with the Heckman selection process described above, a probit model is used to estimate the inverse Mills ratio, but in this case the estimate is a function of household average characteristics and period specific characteristics $\hat{\lambda}_{it} = \frac{\phi(\bar{x}_i^{FE'}, z_{it}, \hat{\delta}_1, \hat{\eta}, \hat{\gamma})}{\Phi(\bar{x}_i^{FE'}, z_{it}, \hat{\delta}_1, \hat{\eta}, \hat{\gamma})}$.

Within-household mean characteristics are estimated using all eight seasonal observations while the regression parameters ($\hat{\delta}_1, \hat{\eta}, \hat{\gamma}, \hat{\lambda}$) are only estimated during the four seasons in which there were sales. For those variables that appear in our estimates twice, as a household mean and a period specific observation, we use the deviation from the mean as the period-specific observation to facilitate interpreting the estimates.

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

Both models are estimated using maximum likelihood. Although effective (discounted) price is included in both selection and demand equations, a dummy variable indicating that the household randomly received a discount coupon is included in the selection equation, but is excluded from the demand equation. The exclusion is valid so long as, conditional on the effective discounted price, the discount coupon serves merely as a reminder of product availability and thus affects the dichotomous purchase decision but has no effect on the continuous choice of insurance coverage, conditional on purchase. Balance checks on the coupons distribution are found in Appendix C.

6 Results and Discussion

In the following discussion, we focus on the estimates generated from the conditional fixed effects model. The coefficient estimates and average marginal effects (AME) of the full model are reported in Table 6 and Table 7, respectively.[25] The average marginal effects are then used to test the four hypothesis. Because the hypothesis are developed with respect to demand broadly, and do not distinguish between the binary purchase decision and the level of purchase, the relevant results from the selection and coverage estimates are presented side-by-side for each hypothesis test. The randomized discount coupon dummy, which is used to identify the selection model, has a strong positive and statistically significant (coef.= 0.284, st. err.=0.083, Table 6) impact on the likelihood of purchasing IBLI.

6.1 General findings

Before testing our hypothesizes, we begin with a short discussion of the relationships between household characteristics and demand, which help to contextualize the somewhat abstract analysis of basis risk and adverse selection.

Referring back to our model of household demand for insurance, we could not analytically sign many of the relationships between household financial characteristics and demand because of the ambiguity of the wealth effect on demand. Empirically we also find mixed responses. HSNP transfers, which reflect an increase to cash income, are associated with an increase in the demand for IBLI. Considering that HSNP transfers are targeted at the poor, it seems reasonable to assume that the cash transfers are helping overcome a liquidity constraint that is limiting uptake among the HSNP target population. At the same time, savings, which are also a form of liquidity, are negatively associated with uptake. The apparent contradiction may reflect a substitution effect between two financial tools—saving and insurance—or a relationship between HSNP targeting and access to savings mechanisms. We are unable to disentangle the two here, but HSNP participants are less likely to have savings than are non-HSNP participants (difference=8.0%, Pearson

[25] The parameter estimates for the pooled model are included in Appendix D as a robustness check. There are few differences in the parameter estimates. Importantly, none of the coefficient estimates used to test our hypothesis changes sign and significance is consistent between the two models in almost every case, and there is no evidence of an increase in precision, which would be indicative that the household average characteristics are superfluous.

$\chi^2(1) = 53.17$). The implication is that HSNP participants are less likely to have cash savings than non-HSNP participants, and that HSNP transfers are associated with increased IBLI demand while savings are associated with a decrease in demand for IBLI.

Households with consistently high participation in social groups have a greater propensity to purchase IBLI. Although participating in social groups could be endogenous to purchasing IBLI, the potential endogeneity is minimized because the household's average participation includes three seasons before the first sales season. Other plausible explanations for the positive relationship between social group participation and IBLI uptake include the complementarities between index insurance and informal idiosyncratic risk pooling described by Mobarak and Rosenzweig (2012) and learning through social networks (Cai, de Janvry & Sadoulet 2011).

There is some indication that demand for IBLI is highest among those with the least amount of risk aversion, and that demand falls as risk aversion increases. Although the coefficient estimates are too imprecise to draw conclusions about the role of risk aversion in demand for IBLI, they are broadly supportive of the literature that frames index insurance uptake a technology uptake. This framing is also supported by the generally low rates of coverage purchased by those that do purchase IBLI. For example, the median coverage rate (TLUs insured/TLUs owned) conditional on IBLI purchase is only about 0.29 in the survey data.

Perhaps, what is most surprising is how unrelated demand and household characteristics are. There are no clear strong monotonic relationships between demand for IBLI and gender, age of the household head, nor do education, income, asset wealth, or ratio of income from livestock, an indicator of the relative risk that drought could pose the household. Herd size, which one might assume would be the key driver of insurance demand, is only statistically significant in one case (lagged herd size on level of coverage purchased) and even there the AME is quite small (AME=0.009, Table 7). Our belief is that the following analysis will provide empirical evidence that the factors identified analytically in Section 2 are able to explain much of the remaining unexplained variation in demand.

6.2 Hypothesis Testing

Hypothesis 1: Demand falls as basis risk increases and the sensitivity of demand to basis risk increases as premiums approach the actuarially fair rate.

Consistent with Hypothesis 1, basis risk has a significant and negative AME on demand, both in uptake (AME=-0.193, St. Err.= 0.116, Table 7) and coverage purchased (AME=-0.793, St. Err.= 0.428, Table 7), conditional on purchasing. The size of the change appears quite large, but the mean of basis risk is only

0.044 and the [minimum, maximum] is [0.00, 0.635]. For example, a rough approximation indicates that increasing basis risk from the mean to the mean plus one standard deviation (0.11) reduces the likelihood of purchase by 2.1 points and coverage by about 0.1 TLU.

Basis risk is interacted with log of the subsidy rate, which is a monotonic transformation of the premium distance from the actuarially fair rate—the variable of interest for Hypothesis 1—because the rate charged is always below the actuarially fair rate. Predictably, premium subsidy rates alone have a strong positive impact on both likelihood of purchasing IBLI coverage and the amount of coverage purchased. At the mean basis risk, the price elasticity of coverage is 1.18, elastic, but becomes inelastic as basis risk increases.[26]

Hypothesis 1 states basis risk should become more important as the subsidies fall and the price approaches the actuarially fair rate. Contradicting Hypothesis 1, sensitivity to basis risk seems to increase with basis risk, although the change is not statistically significant within one standard deviation of the mean subsidy rate (Table 8). Explicitly, increasing basis risk always reduces demand, but there is weak evidence that it does so at a greater rate for those with higher subsidies, which contradicts the second part of Hypothesis 1. We have no evidence as to why this might be, but one plausible theory is that potential clients under-estimate the (actuarially fair) value of the product to the extent that they treat it as though the premium rates are above the actuarially fair rate.

Hypothesis 2: As households' knowledge of the product improves, they will become more responsive to actual basis risk.

The impact of IBLI knowledge on demand response to basis risk is tested by interacting basis risk with an indicator that the head of household played the randomized education game described in the research design section. Participation in the game had a strongly positive and significant impact on performance on the IBLI knowledge test (Row 1, Table 5), even among those that never purchased IBLI (Row 2, Table 5). Note as well that playing the game directly increases IBLI uptake (Coef.=0.302, St. Err.=0.116, Table 6) and level of purchase (Coef.=0.216, St. Err.=0.0939, Table 6).

The exogenous increase to IBLI knowledge, by way of participation in the randomized educational game, increases sensitivity to basis risk considerably (Table 9). In fact, among those that were not randomly selected to play the educational game, there seems to be very little relationship between basis risk and demand. These findings indicate that (A) the educational extension games were an effective form of extension and (B), there is a grave need for further investments in educational campaigns.[27]

[26] Mean basis risk is equal to 0.044, the coefficient estimate for the natural log of the subsidy rate is1.25, and the coefficient estimate for the natural log of the subsidy rate interacted with basis risk is equal to -1.64.

[27] A further analysis, which is not included here, reveals that the impacts of the one-shot educational game on responsiveness to basis risk do not dissipate during the four seasons examined in this analysis.

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

Households' reported expectation of next season's rangeland conditions and *Pre-Czndvi* (a division level proxy for rangeland conditions at the time of sale) are used to test for inter-temporal adverse selection.

There is evidence that households adjust demand in response to signals of the coming conditions, but the adjustments are not entirely consistent with each other or with our hypothesis. The sign on the coefficient estimates associated with an expectation that conditions will be good is negative, which is consistent with our hypothesis but the estimates are not statistically significant. An expectation that the rangeland will be worse than normal during the coming (insurance) season are statistically significant and negatively related to IBLI demand.[28] While, at the same time, households are less (more) likely to purchase coverage during seasons in which the NDVI index indicates that conditions were good (poor) during the purchase window, and those that do, purchase less (more) coverage. Although the magnitude of the average marginal effect is small, *Pre-Czndvi* is distributed around zero and ranges from -21.52 to 14.92, so that its effects on coverage are considerable in seasons when conditions are extremely poor or favorable. For example, as households entered the SRSD11 drought season, which triggered indemnity payments in all IBLI regions, the average *Pre-Czndvi* value was -17.48, which would be associated with a three point increase in likelihood of purchasing insurance (AME=-0.0018, Table 7) and a 5% increase in coverage purchased, conditional on purchasing (AME=-0.0087, Table 7).

The contradiction between the role of expected conditions and pre-CZNDVI could be reflecting a distinction between the rangelands that a household commonly uses, and thus respond on in the survey, and their index region. Such a distinction is realistic. For example, many of the communities in the data have designated wet and dry season pastures, which would usually represent a region that is negligible when compared to the entire index region. Add to that, that households often hold some of their animals with relatives in far off regions, which could be in a completely different index region, and it is not surprising that a pastoralist might report on rangelands that are not bounded by boundaries of their index region.

Another, perhaps clearer, way to interpret these findings are that pastoralists are more likely to insure when there are signals of covariate threats (division average patterns of forage availability are worse than normal) and less likely to purchase insurance when they perceive an increased threat of an idiosyncratic shock to their forage availability.

For insurance providers, such intertemporal adverse selection is of grave concern. Here, one of the very index factors that directly leads to indemnity payments is also related to insurance uptake. Furthermore,

[28] Note as well that households with a generally pessimistic opinion of conditions, in that they expect poor conditions more often than normal, purchase more coverage (AME=0.458, St. Err.=0.175, Table 7).

there is a strong argument that division-scale rangeland conditions are exogenous to individual actions and capture conditions just as potential clients are making their purchase decision, which points towards a causal relationship In this case, pre-CZNDVI has a causal impact on demand for IBLI and on indemnity payments and that relationship increases demand in periods in which indemnities are made.

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

Confirming Hypothesis 4, there is strong evidence of spatial adverse selection. The AME of division-level basis risk is negative for both uptake (AME=-1.20, St. Err.=0.367, Table 7) and coverage (AME=-3.59, St. Err.=1.596, Table 7). Those divisions with greater basis risk consistently face lower demand. There is also some evidence that demand is higher in divisions with higher livestock mortality rates on average.

The division average basis risk variable is interacted with the IBLI extension game in order to allow its effects to vary across understanding of IBLI. Similar to the findings on household-level basis risk, those that participated in the IBLI extension game respond much more strongly than those that did not (Table 10). The implication of increased sensitivity to basis risk associated understanding of the product for spatial adverse selection is that as clients become more familiar with a product, they respond more strongly to product quality. In cases that the quality varies across index regions, index insurance providers will see an increase in heterogeneity in demand across space as prospective clients become more product savvy.

As discussed earlier, spatial heterogeneity in demand across index regions is only of an immediate concern to insurance providers that lump index regions together in order to homogenize premium rates and simplify insurance contracts, as they did with IBLI. For those with development or humanitarian objectives, a potential concern is that, if there is a negative correlation between poverty and high-quality data availability with which to develop high-quality insurance products, the correlation could lead to a market equilibrium with low quality products and low demand for insurance in marginal regions with high poverty rates. Such welfare reducing market equilibrium are discussed by Clarke and Wren-Lewis (2013). A second implication is that the public sector should continue to be active in extension and product education efforts as the private sector may have a conflict of interest.

6.3 *Shapley's R^2 Decomposition*

A Shapley's R^2 decomposition sheds some light on which factors contribute most to explaining variation in IBLI uptake and level of purchase. To do so, we use a two-stage model, rather than the maximum likelihood model used in the main analysis.[29] The goodness of fit measures for each stage are decomposed according to pre-specified groups of variables using an adjusted version of the user-written STATA command *shapely2* (Juárez 2014), which builds off earlier work by Kolenikov (2000) and theory by Shapley (1953) and Shorrocks (2013).[30] The Shapley R^2 decompositions should be interpreted as the ratio of the model's goodness of fit (R^2 or Pseudo R^2) that can be attributed to each group of variables.

Table 11 presents the Shapley R^2 decompositions by group. Household characteristics account for under half of the variation in demand and price accounts for between 10% and 14% of the variation. Basis risk and knowledge are more important for uptake than demand, accounting for 9% and 5% of the observed variation, respectively. Both intertemporal and spatial adverse selection are also more important for a households' uptake decision than for their coverage decision. In addition, there is very strong evidence that the selection process is very important to consider when examining index insurance demand. The inverse Mills ratio accounts for over 30% of the fit our second stage of our two-stage model. Altogether, the main variables of interest that were used to test our four hypothesis are responsible for 30% and 25% of the uptake and coverage decisions that households make, respectively.

6.4 Concluding Remarks

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

With the model estimates and Shapely values in mind, it is clear that both product and household characteristics play an important role in determining demand for index insurance. While little can be done to change household characteristics, it may be possible to improve contract design to lessen adverse selection and basis risk. For example, IBLI no longer aggregates index divisions into premium regions, removing one source of spatial adverse selection. Adjusting premium rates dynamically to account for initial season conditions is an additional step that could be taken to reduce adverse selection. Idiosyncratic risk, a component of basis risk, limits the potential impact of even a perfect index product, but is in part a construct of the index division, which is now being be adjusted to increase the importance of covariate risk.

---

[29] A side-by-side comparison of the pooled two-stage and pooled maximum likelihood estimates, as well as the full Shapley's R^2 decomposition are found in Appendix E. Importantly, the coefficient estimates are very similar between the two models.

[30] The variable categories are demographic, financial, price, basis risk and knowledge, intertemporal adverse selection, spatial adverse selection, and a category containing either the instrumental variable or the inverse Mills ratio.

Reducing design risk is likely to be relatively simple if household-level data are collected and used to improve the performance of the index. Finally, improving understanding of the IBLI product through extension increases demand for IBLI and redistributes that demand to those with the least basis risk, improving the likelihood that the product will successfully cover risk and benefit its clients. The evidence from the IBLI pilot in northern Kenya clearly underscore the importance of index insurance design to resulting demand patterns for these innovative financial instruments.

REFERENCES

Barnett, Barry J, Christopher B Barrett, and Jerry R Skees. 2008. Poverty Traps and Index-Based Risk Transfer Products. *World Development* 36 (10):1766-1785.

Barnett, Barry J, and Olivier Mahul. 2007. Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries. *American Journal of Agricultural Economics* 89 (5):1241-1247.

Barrett, Christopher, Barry J Barnett, Michael Carter, Sommarat Chantarat, James Hansen, Andrew Mude, Daniel Osgood, Jerry Skees, Calum Turvey, and M Neil Ward. 2007. Poverty Traps and Climate risk: Limitations and Opportunities of Index-Based Risk Financing. IRI Technical Report 07-02

Barrett, Christopher B, Paswel Phiri Marenya, John McPeak, Bart Minten, Festus Murithi, Willis Oluoch-Kosura, Frank Place, Jean Claude Randrianarisoa, Jhon Rasambainarivo, and Justine Wangila. 2006. Welfare Dynamics in Rural Kenya and Madagascar. *The Journal of Development Studies* 42 (2):248-277.

Barrett, Christopher B, and Paulo Santos. 2014. The Impact of Changing Rainfall Variability on Resource-Dependent Wealth Dynamics. *Ecological Economics* 105 (1):48-54.

Binswanger-Mkhize, Hans P. 2012. Is there too much Hype about Index-Based Agricultural Insurance? *Journal of Development Studies* 48 (2):187-200.

Boucher, Stephen R, Michael R Carter, and Catherine Guirkinger. 2008. Risk Rationing and Wealth Effects in Credit Markets: Theory and Implications for Agricultural Development. *American Journal of Agricultural Economics* 90 (2):409-423.

Cai, Jing, Alain de Janvry, and Elisabeth Sadoulet. 2011. Social Networks and Insurance Take Up: Evidence from a Randomized Experiment in China. *ILO Microinsurance Innovation Facility Research Paper* (8).

Carriquiry, Miguel A, and Daniel E Osgood. 2012. Index Insurance, Probabilistic Climate Forecasts, and Production. *Journal of Risk and Insurance* 79 (1):287-300.

Chamberlain, Gary. 1980. Analysis of Covariance with Qualitative Data. *The Review of Economic Studies* 47 (1):225-238.

Chantarat, Sommarat, Christopher B Barrett, Andrew G Mude, and Calum G Turvey. 2007. Using Weather Index Insurance to Improve Drought Response for Famine Prevention. *American Journal of Agricultural Economics* 89 (5):1262-1268.

Chantarat, Sommarat, Andrew G Mude, and Christopher B Barrett. 2009. Willingness to Pay for Index Based Livestock Insurance: Results from a field Experiment in Northern Kenya. Unpublished.

Chantarat, Sommarat, Andrew G Mude, Christopher B Barrett, and Michael R Carter. 2013. Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya. *Journal of Risk and Insurance* 80 (1):205-237.

Chantarat, Sommarat, Andrew G Mude, Christopher B Barrett, and Calum G Turvey. 2014. The Performance of Index Based Livestock Insurance: Ex Ante Assessment in the Presence of a Poverty Trap. Unpublished.

Clarke, D. J. (2016). A theory of rational demand for index insurance. *American Economic Journal: Microeconomics*, *8*(1), 283-306.

Clarke, D. J., & Wren-Lewis, L. (2013). Learning from Lemons: The Role of Government in Index Insurance for Individuals. *FERDI Policy Brief*, (70).

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Robert Townsend, Petia Topalova, and James Vickery. 2013. Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied economics* 5 (1):104.

Cragg, John 1971. Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica* 39 (5):829-844.

Dercon, Stefan, Ruth Hill, Daniel Clarke, Ingo Outes-Leon, and Alemayehu Taffesse. 2014. Offering Rainfall Insurance to Informal Insurance Groups: Evidence from a Field Experiment in Ethiopia. *Journal of Development Economics* 106:132-143.

Food and Agriculture Organization, (FAO). 1999. Livestock and Environment Toolbox: Food and Agriculture Organization (FAO). http://www.fao.org (accessed May 2014).

Giné, Xavier, Robert Townsend, and James Vickery. 2008. Patterns of Rainfall Insurance Participation in Rural India. *The World Bank Economic Review* 22 (3):539-566.

Giné, Xavier, and Dean Yang. 2009. Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi. *Journal of Development Economics* 89 (1):1-11.

Greene, William. 2004. The Behaviour of the Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects. *The Econometrics Journal* 7 (1):98-119.

Hazell, Peter, and Ulrich Hess. 2010. Drought Insurance for Agricultural Development and Food Security in Dryland Areas. *Food Security* 2 (4):395-405.

Heckman, James J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47 (1):153-161.

Hellmuth, Molly, Daniel Osgood, Ulrich Hess, Anne Moorhead, and Haresh Bhojwani, eds. 2009. *Index Insurance and Climate risk: Prospects for Development and Disaster Management*: Climate and

Society No. 2. International Research Institute for Climate and Society (IRI), Columbia University, New York, USA.

Hess, Ulrich, Jerry Skees, Andrea Stoppa, Berry Barnett, and John Nash. 2005. Managing Agricultural Production Risk: Innovations in Developing Countries. *Agriculture and Rural Development (ARD) Department Report* (32727-GLB).

Hill, Ruth Vargas, Miguel Robles, and Francisco Ceballos. 2013. *Demand for Weather Hedges in India: An Empirical Exploration of Theoretical Predictions*. Vol. 1280: Intl Food Policy Res Inst.

Hurrell, Alex, and Rachel Sabates-Wheeler. 2013. Kenya Hunger Safety Net Programme Monitoring and Evaluation Component: Quantitative Impact Evaluation Final Report: 2009 to 2012. Oxford Policy Management.

International Livestock Research Institute, (IRLI). 2012. *Index Based Livestock Insurance for Northeastern Kenya's Arid and Semi-Arid Lands: The Marsabit Pilot Project-Codebook for IBLI Evaluation Baseline Survey*. Nairobi, Kenya: ILRI.

Janzen, Sarah A, Michael R Carter, and Munenobu Ikegami. 2013. Valuing Asset Insurance in the Presence of Poverty Traps. Unpublished.

Jensen, Nathaniel D, Christopher B Barrett, and Andrew G Mude. 2016a. Index Insurance Quality and Basis Risk: Evidence from Northern Kenya. *AJAE*, forthcoming.

Jensen, Nathaniel D, Christopher B Barrett, and Andrew G Mude. 2016b. Index Insurance and Cash Transfers: A Comparative Analysis from Northern Kenya. Unpublished.

Juárez, F. 2014. shapely2. STATA user-written command.

Karlan, D, R Osei, I Osei-Akoto, and C Udry. 2014. Agricultural Decisions after Relaxing Risk and Credit Constraints. *Quarterly Journal of Economics* 129 (2):597-652.

Kolenikov, S., & Shorrocks, A. 2005. A decomposition analysis of regional poverty in Russia. *Review of Development Economics*, 9(1), 25-46.

Leblois, Antoine, and Philippe Quirion. 2013. Agricultural Insurances Based on Meteorological Indices: Realizations, Methods and Research Challenges. *Meteorological Applications* 20 (1):1-9.

Liu, Yanyan, and Robert Myers. 2012. The Dynamics of Insurance Demand Under Liquidity Constraints and Insurer Default Risk. *International Food Policy Research Institute (IFPRI)*.

Lybbert, Travis J., Christopher Barrett, Solomon Desta, and D. Layne Coppock. 2004. Stochastic Wealth Dynamics and Risk Management Among a Poor Population. *The Economic Journal* 114 (498):750-777.

Lybbert, Travis J, David R Just, and Christopher B Barrett. 2013. Estimating Risk Preferences in the Presence of Bifurcated Wealth Dynamics: Can we Identify Static Risk Aversion Amidst Dynamic Risk Responses? *European Review of Agricultural Economics* 40 (2):361-377.

Mahul, Olivier, and Jerry R Skees. 2007. Managing Agricultural Risk at the Country Level: The Case of Index-Based Livestock Insurance in Mongolia. *World Bank Policy Research Working Paper* (4325).

McIntosh, Craig, Alexander Sarris, and Fotis Papadopoulos. 2013. Productivity, Credit, Risk, and the Demand for Weather Index Insurance in Smallholder Agriculture in Ethiopia. *Agricultural Economics* 44 (4-5):399-417.

McPeak, John. 2006. Confronting the Risk of Asset Loss: What Role do Livestock Transfers in Northern Kenya Play? *Journal of Development Economics* 81 (2):415-437.

McPeak, John G, and Christopher B Barrett. 2001. Differential Risk Exposure and Stochastic Poverty Traps among East African Pastoralists. *American Journal of Agricultural Economics* 83 (3):674-679.

McPeak, John, Sommarat Chantarat, and Andrew Mude. 2010. Explaining Index-Based Livestock Insurance to Pastoralists. *Agricultural Finance Review* 70 (3):333-352.

McPeak, John, Peter Little, and Cheryl Doss. 2011. *Risk and Social Change in an African Rural Economy: Livelihoods in Pastoralist Communities*: Routledge.

Miranda, Mario J, and Katie Farrin. 2012. Index Insurance for Developing Countries. *Applied Economic Perspectives and Policy* 34 (3):391-427.

Mobarak, Ahmed Mushfiq, and Mark R Rosenzweig. 2012. Selling Formal Insurance to the Informally Insured. Unpublished.

Mundlak, Yair. 1978. On the Pooling of Time Series and Cross Section Data. *Econometrica* 46 (1):69-85.

Pratt, Anthony, Pablo Suarez, and Ulrich Hess. 2010. How do Small-Holder Farmers Understand Insurance, and How Much do They Want it? Evidence from Africa. *Global Environmental Change* 20 (1):153-161.

Santos, Paulo, and Christopher B Barrett. 2011. Persistent Poverty and Informal Credit. *Journal of Development Economics* 96 (2):337-347.

Shapley, Lloyd. 1953. A Value for n-person Games. In *Contributions to the Theory of Games*, edited by H. W. Kuhn and A. W. Tucker: Princeton University Press.

Shorrocks, Anthony F. 2013. Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley value. *Journal of Economic Inequality* 11 (1):1-28.

Skees, Jerry R, and Benjamin Collier. 2008. The Potential of Weather Index Insurance for Spurring a Green Revolution in Africa. *Global Ag Risk Inc*.

Skees, Jerry R, Jason Hartell, JQ Hao, A Sarris, and D Hallam. 2006. Weather and Index-Based Insurance for Developing Countries: Experience and Possibilities. In *Agricultural Commodity Markets and Trade: New Approaches to Analyzing Market Structure and Instability*, edited by A. Sarris and D. Hallam. Northampton, MA: Edward Elgar.

Smith, Vince, and Myles Watts. 2009. Index based Agricultural Insurance in Developing Countries: Feasibility, Scalability and Sustainability. Report to the Gates Foundation.

Tobin, James. 1958. Estimation of Relationships for Limited Dependent Variables. *Econometrica* 26 (1):24-36.

Wooldridge, Jeffrey M. 1995. Selection Corrections for Panel Data Models Under Conditional Mean Independence Assumptions. *Journal of Econometrics,* 68 (1):115-132.

FIGURES

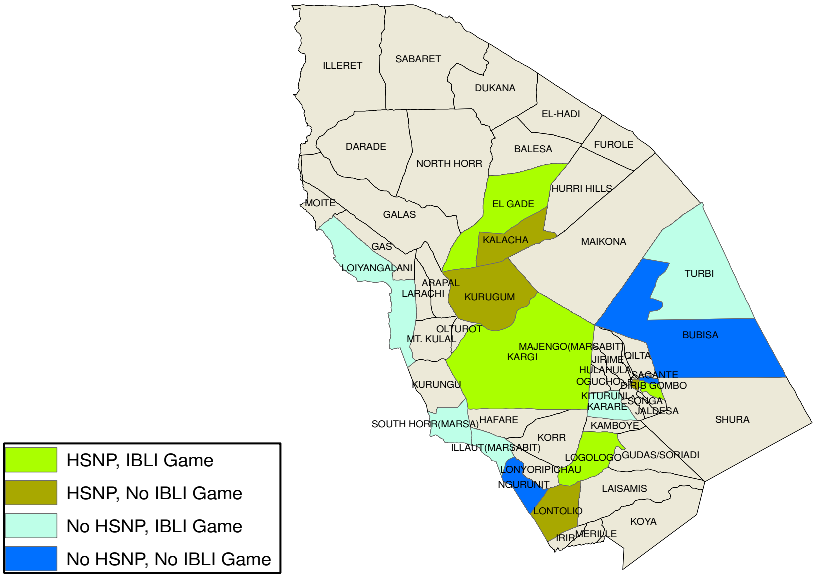

Figure 1. *Survey Design, Participation in IBLI Game and HSNP Target Sites*

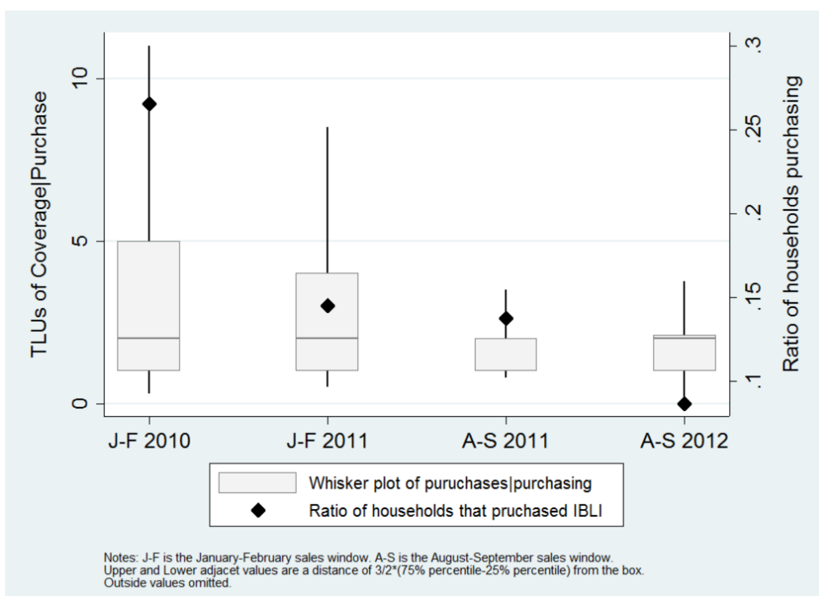

Figure 2. *IBLI Purchasing Behavior During Each Sales Window*

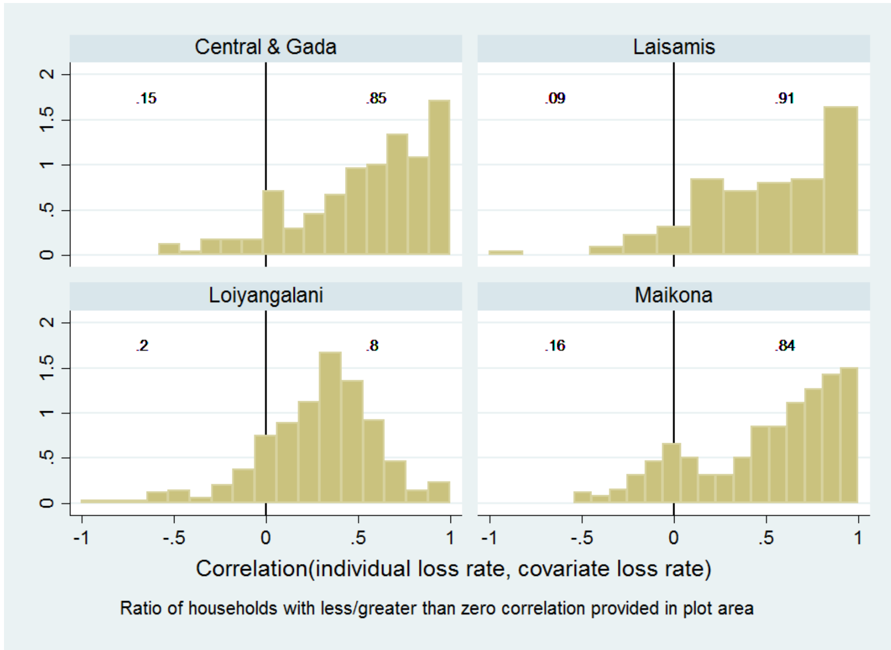

Figure 3. *Histograms of the Correlation between Individual and Covariate Livestock Mortality Rates*

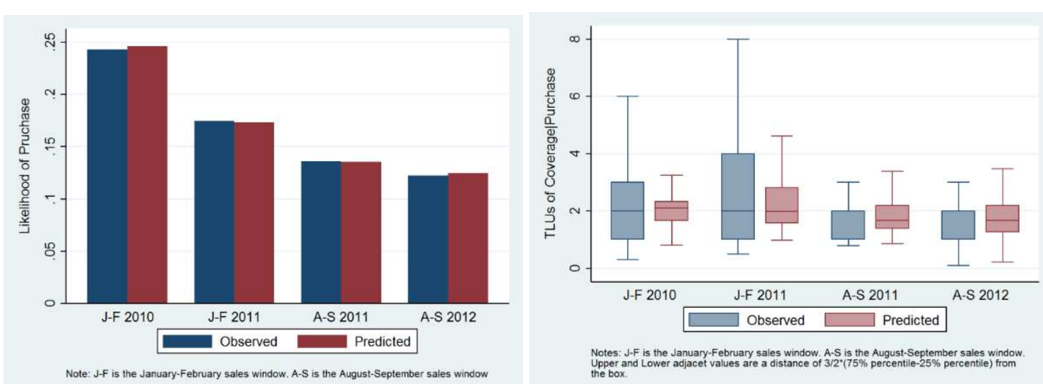

Figure 4. *Unconditional Observed and Predicted Likelihood of Purchasing IBLI (Left) and Level of Purchases, Conditional on Being a Purchaser (Right)*

TABLES

Table 1

Representation of Demand for IBLI in the Survey Sample

Survey#	Sales Window	IBLI Coverage Period		Total Contracts Sold in Population	IBLI survey households: Did Not Purchase	IBLI survey households: Purchased
R1 (2009)	-	-		-	-	-
	-	-		-	-	-
R2 (2010)	J-F 2010	LRLD10/SRSD10	(N)	1,974	679	245
			(Mean) &	3.0	-	(3.94)
	None	-	(N)	-	-	-
			(Mean) &	-	-	-
R3 (2011)	J-f 2011	LRLD11/SRSD11	(N)	595	790	134
			(Mean) &	(2.1)	-	(3.05)
	A-S 2011	SRSD11/LRLD12	(N)	509	797	127
			(Mean) &	(1.6)	-	(2.39)
R4 (2012)	None	-	(N)	-	-	-
			(Mean) &	-	-	-
	A-S 2012	SRSD12/LRLD13	(N)	216	844	80
			(Mean) &	(1.9)	-	(2.29)

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

Table 2

Household IBLI Purchase Patterns Among Survey Households, By Sales Window

Sales window	New[1]	Replacement[2]	Augmenting[3]	Holding[4]	Reenter[5]	Lapsed[6]	Total[7]
J-F 2010	225	0	0	0	0	0	225
J-F 2011	67	60	0	0	0	165	292
A-S 2011	66	0	31	96	21	144	358
A-S 2012	19	25	0	0	33	300	377

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

Table 3

The Average Observed Design Error in Each Division at Each Sales Period

Sales Seasons	Design Risk Observations	Observed Average Estimated Design Error (X100) Central/Gadamoji	Laisamis	Loiyangalani	Maikona
J-F 2010	-	0	0	0	0
J-F 2010	LRLD 2010	4.69	6.37	7.66	2.61
A-S 2011	LRLD 2010, SRSD 2010	8.53	6.56	8.16	3.95
A-S 2012	LRLD 2010, SRSD 2010, LRLD 2011, SRSD11	5.93	4.22	7.67	3.12

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

Table 4

Rangeland Conditions During Each Sales Window as Predictors of Final Index Value

Variable	Index	Index	Index
Pre-Czndvi	-0.0066**		-0.0059***
	(0.0024)		(0.0001)
Expected Rangeland Condition[1]:			
Good		-0.0382***	-0.0220***
		[0.0032]	[0.0026]
Bad		0.0467***	0.0386***
		[0.0041]	[0.0037]
Constant	0.0769**	0.1153***	0.0794***
	(0.0262)	[0.0018]	[0.0016]
Observations	16	3,696	3,696
R-squared	0.3594	0.0901	0.3648

Notes: [1]The expected conditions variables are a set of dummy variables for expected conditions are: good, normal, or bad. *Expected conditions=Normal* is the omitted category. Standard errors in parentheses. Household clustered and robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 5

The Impact of the Randomized Extension Game on Understanding of the IBLI Contracts

	Not game participant		Game participant			
IBLI Knowledge:	Mean	Std. Err.	Mean	Std. Err.	Difference	t-test
Full Sample (N=832)	1.73	0.043	2.12	0.072	0.39	4.65***
Never Purchased (N=450)	1.55	0.055	1.88	0.107	0.34	2.82***

Notes: The game was played in January 2010. The scores above reflect the number of correct answers to survey questions testing household understanding of IBLI contract details. Significance is indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table 6

Coefficient Estimates on Demand for IBLI (Conditional FE Model)

	Uptake		Level (TLU)	
VARIABLES	Coefficient	Std. Err.	Coefficient	Std. Err.
Household Period-Specific Characteristics:				
Male [A]	0.0226	(0.0907)	0.0824	(0.0836)
Age [A]	-0.0080*	(0.0048)	-0.0069	(0.0048)
Age^2 [A]	0.0000	(0.0002)	0.0001	(0.0002)
Education [A]	0.0147	(0.0432)	0.0328	(0.0388)
Dependency Ratio [A]	0.7795**	(0.3335)	0.5702	(0.3535)
Social Groups [A]	0.0494	(0.0553)	0.0278	(0.0486)
Ln(income) [A]	0.0348	(0.0285)	0.0322	(0.0249)
$Ln(income)^2$ [A]	0.0095**	(0.0047)	0.0053	(0.0040)
Ratio income livestock [A]	-0.1600	(0.1404)	-0.2280*	(0.1331)
TLU [A]	0.0061	(0.0041)	0.0088**	(0.0036)
TLU^2 [A]	-0.0002	(0.0001)	-0.0001	(0.0001)
Asset Index	-0.1805*	(0.1039)	-0.0510	(0.0801)
Savings (10TLU) [A]	-0.3485**	(0.1717)	-0.1735	(0.1609)
HSNP [A]	0.3207*	(0.1722)	0.2681*	(0.1416)
HSNP Eligible [A]	0.1037	(0.1980)	-0.0333	(0.2023)
Discount Coupon (=1 if recipient)	0.2858***	(0.0883)		
Household Averages Characteristics:				
Age	-0.0012	(0.0137)	-0.0037	(0.0113)
Age^2	0.0000	(0.0001)	0.0000	(0.0001)
Education	-0.0199*	(0.0119)	-0.0106	(0.0107)
Dependency Ratio	-0.3074	(0.2455)	-0.3625	(0.2373)
Social Groups	0.4786***	(0.0713)	0.3245***	(0.0758)
Ln(income)	-0.0012	(0.1568)	-0.0998	(0.1511)
$Ln(income)^2$	0.0006	(0.0120)	0.0090	(0.0117)
Ratio income livestock	0.0241	(0.1719)	-0.0741	(0.1959)
TLU	-0.0020	(0.0062)	0.0072	(0.0065)
TLU^2	-0.0000	(0.0001)	-0.0002**	(0.0001)
Asset Index	0.0490	(0.0745)	0.1180	(0.0780)
Savings (10TLU)	0.0470	(0.2528)	-0.3855	(0.2488)
HSNP	-0.1311	(0.1884)	-0.0254	(0.1784)
HSNP Eligible	-0.0783	(0.1941)	-0.0380	(0.1898)
HSNP Village	0.0673	(0.1201)	-0.0348	(0.1324)
Moderately Risk Averse	-0.0444	(0.0931)	-0.0337	(0.0832)
Extremely Risk Averse	-0.1902*	(0.1040)	-0.1105	(0.0924)
Risk	-0.8503*	(0.5083)	-0.6441	(0.4690)
Expected Conditions: Good=1	0.0803	(0.1678)	0.2127	(0.1431)
Expected Conditions: Bad=1	-0.0136	(0.1898)	0.4579***	(0.1751)
Hypothesis 1: Basis Risk And Price				
Basis Risk	-0.9527	(1.2988)	-1.1880	(1.1407)
Ln (Subsidy)	0.9684***	(0.2881)	1.2544***	(0.2129)
Basis Risk x Ln (Subsidy)	-1.8647	(2.1765)	-1.6360	(1.9513)
Hypothesis 2: Basis Risk And Learning				
Game	0.3024***	(0.1160)	0.2161**	(0.0939)
Basis Risk X Game	-2.6114**	(1.2046)	-1.4809	(1.0525)
Hypothesis 3: Intertemporal Adverse Selection				
Expected Conditions: Good=1 [B]	-0.0825	(0.0979)	-0.1053	(0.0845)
Expected Conditions: Bad=1 [B]	-0.2477**	(0.1035)	-0.2514**	(0.0999)
Pre-CZNDVI	-0.0085*	(0.0046)	-0.0087*	(0.0046)
Hypothesis 4: Spatial Adverse Selection				
Division Average Loss Rate	5.6283**	(2.7645)	3.9716	(2.6839)
Division Average Basis Risk	-4.8524**	(1.9611)	-2.4986	(1.8095)
Division Average Basis Risk X Game	-2.2374	(2.5614)	-3.6911*	(2.1707)
Observations				3,096
Wald test of Independent Equations χ^2				177.45
Model Wald χ^2				174.49

Notes: Additional covariates not listed above include time dummies and a constant. [A] Variable is demeaned and lagged one period. [B] Variable is demeaned. [#]Omitted variable is E*xpected conditions: poor*. Household clustered and robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 7

Average Marginal Effects (AME) on Demand for IBLI (Conditional FE Model)

	Uptake		Level (TLU)	
VARIABLES	AME	Std. Err.	AME	Std. Err.
Household Period-Specific Characteristics:				
Male [A]	0.0049	(0.0197)	0.0824	(0.0836)
Age [A]	-0.0017*	(0.0010)	-0.0068	(0.0049)
Education [A]	0.0032	(0.0094)	0.0328	(0.0388)
Dependency Ratio [A]	0.1695**	(0.0734)	0.5702	(0.3535)
Social Groups [A]	0.0107	(0.0120)	0.0278	(0.0486)
Ln(income) [A]	0.0085	(0.0066)	0.0360	(0.0269)
Ratio income livestock [A]	-0.0348	(0.0303)	-0.2280*	(0.1331)
TLU [A]	0.0014	(0.0009)	0.0090**	(0.0037)
Asset Index [A]	-0.0393*	(0.0226)	-0.0510	(0.0801)
Savings (10TLU) [A]	-0.0758**	(0.0374)	-0.1735	(0.1609)
HSNP [A]	0.0698*	(0.0376)	0.2681*	(0.1416)
HSNP Eligible [A]	0.0226	(0.0430)	-0.0333	(0.2023)
Discount Coupon (=1 if recipient)	0.0622***	(0.0194)		
Household Averages Characteristics:				
Age	0.0003	(0.0007)	0.0011	(0.0029)
Education	-0.0043*	(0.0026)	-0.0106	(0.0107)
Dependency Ratio	-0.0669	(0.0538)	-0.3625	(0.2373)
Social Groups	0.1041***	(0.0154)	0.3245***	(0.0758)
Ln(income)	0.0018	(0.0103)	0.0345	(0.0434)
Ratio income livestock	0.0052	(0.0374)	-0.0741	(0.1959)
TLU	-0.0006	(0.0010)	0.0012	(0.0044)
Asset Index	0.0107	(0.0162)	0.1180	(0.0780)
Savings (10TLU)	0.0102	(0.0550)	-0.3855	(0.2488)
HSNP	-0.0285	(0.0411)	-0.0254	(0.1784)
HSNP Eligible	-0.0170	(0.0422)	-0.0380	(0.1898)
HSNP Village	0.0146	(0.0262)	-0.0348	(0.1324)
Moderately Risk Averse	-0.0097	(0.0203)	-0.0337	(0.0832)
Extremely Risk Averse	-0.0414*	(0.0225)	-0.1105	(0.0924)
Risk	-0.1849*	(0.1113)	-0.6441	(0.4690)
Expected Conditions: Good=1 [B]	0.0175	(0.0365)	0.2127	(0.1431)
Expected Conditions: Bad=1 [B]	-0.0030	(0.0413)	0.4579***	(0.1751)
Hypothesis 1: Basis Risk And Price				
Basis Risk	-0.1933*	(0.1155)	-0.7933*	(0.4277)
Ln (Subsidy)	0.1960***	(0.0581)	1.1796***	(0.1887)
Hypothesis 2: Basis Risk And Learning				
Game	0.0283	(0.0187)	-0.0147	(0.0729)
Hypothesis 3: Intertemporal Adverse Selection				
Expected Conditions: Good=1 [B, C]	-0.0179	(0.0213)	-0.1053	(0.0845)
Expected Conditions: Bad=1 [B, C]	-0.0539**	(0.0227)	-0.2514**	(0.0999)
Pre-CZNDVI	-0.0018*	(0.0010)	-0.0087*	(0.0046)
Hypothesis 4: Spatial Adverse Selection				
Division Average Loss Rate	1.2242**	(0.6057)	3.9716	(2.6839)
Division Average Basis Risk	-1.2044***	(0.3664)	-3.5889**	(1.5961)
Observations				3,096
Wald Test of Independent Equations χ^2				177.45
Model Wald χ^2				174.49

Notes: Additional covariates not listed above include time dummies and a constant. [A] Variable is demeaned and lagged one period. [B] Omitted variable is E*xpected conditions: normal*. [C] Variable is demeaned. Household clustered and robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 8

The AME of Basis Risk on Demand Across Premium Discounts

Subsidy (Subsidy Rate)	AME of basis risk	Std. Err.	t-stat	P>t	[95% Conf. Interval]	
Probit						
Mean – 1SD (50.1%)	-0.0899	(0.1294)	-0.6950	0.4870	-0.3435	0.1637
Mean (60.3%)	-0.1776	(0.1162)	-1.5285	0.1264	-0.4053	0.0501
Mean + 1SD (72.5%)	-0.2861*	(0.1602)	-1.7862	0.0741	-0.6001	0.0278
Level						
Mean – 1SD (50.1%)	-0.4963	(0.5646)	-0.8789	0.3794	-1.6030	0.6104
Mean (60.3%)	-0.7972*	(0.4278)	-1.8635	0.0624	-1.6358	0.0413
Mean + 1SD (72.5%)	-1.0982**	(0.5523)	-1.9886	0.0468	-2.1807	-0.0158

Notes: The mean within-survey estimated actuarially fair rate is 8.3%. IBLI contracts were marketed at an average rate of 3.9% before any discounts were applied.

Table 9

The Impact of IBLI Education on Demand Sensitivity to Basis Bisk

Played Game	AME of basis risk	Std. Err.	t-stat	P>t	[95% Conf. Interval]	
Probit						
No	-0.0201	(0.1308)	-0.1536	0.8779	-0.2765	0.2363
Yes	-0.6064**	(0.2385)	-2.5426	0.0110	-1.0739	-0.1390
Level						
No	-0.3549	(0.4853)	-0.7314	0.4645	-1.3060	0.5962
Yes	-1.8390**	(0.9150)	-2.0097	0.0445	-3.6324	-0.0455

Table 10

The Relationship between Demand for IBLI, Division-Average Basis Risk, and IBLI Knowledge

Played Game	AME of Division-Average Basis Risk	Std. Err.	t-stat	P>t	[95% Conf. Interval]	
Probit						
No	-1.0395**	(0.4167)	-2.4944	0.0126	-1.8563	-0.2227
Yes	-1.5976***	(0.5076)	-3.1473	0.0016	-2.5925	-0.6027
Level						
No	-2.4986	(1.8095)	-1.3808	0.1673	-6.0450	1.0479
Yes	-6.1897***	(2.0249)	-3.0568	0.0022	-10.1584	-2.2209

Table 11

Shapley Decomposition of Pseudo R^2 and R^2 (%)

	IBLI Uptake (Probit)	Level of Purchase (Conditional on Purchase)
Household Characteristics:		
Demographics [A]	29.93	22.68
Financial [B]	17.95	14.70
Product Related Characteristics:		
Subsidy [C]	10.94	13.04
Basis Risk & Knowledge [D]	9.13	4.62
Prospective Adverse Selection:		
Intertemporal [E]	5.31	2.61
Spatial [F]	4.78	4.05
Coupon Dummy/IMR	21.95	38.30
Total	100.00	100.00
(Pseudo R^2) [R^2]	(0.132)	[0.418]

[A] Includes: gender, age, age^2, education, dependency ratio, social groups, level of risk aversion, HSNP eligibility, HSNP village, and the within household means of each of the afore mentioned, where there is within household variation.

[B] Includes: ln(income), ln(income)^2, ratio income from livestock, TLU, TLU^2, asset index, Savings(10TLU), HSNP, and the within household means of each of the afore mentioned

[C] Includes: ln(subsidy rate).

[D] Includes: basis risk, game, basis risk X ln(subsidy rate), basis risk X game.

[E] Includes: expected conditions dummies, Pre-Czndvi

[F] Includes: division average livestock mortality rate, division-period average basis risk, division-period average basis risk X game.

How Basis Risk and Spatiotemporal Adverse Selection Influence Demand for Index Insurance: Evidence from Northern Kenya

— For Online Publication—

Nathaniel D. Jensen
Cornell University

Andrew G. Mude
International Livestock Research Institute

Christopher B. Barrett
Cornell University

Contents:

Corresponding author: Nathaniel Jensen, Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14850; ndj6@cornell.edu

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

The risk:

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

The index:

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

Contract strike level:

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

Geographical coverage of contract and the index:

Marsabit District is covered by two separate contracts. There is an Upper Marsabit contract consisting of Maikona and North Horr divisions, and a Lower Marsabit contract consisting of Central, Gadamoji, Laisamis, and Loiyangalani divisions (Figure A1).

The index – predicted livestock mortality – computed and reported at the division level. The five division—North Horr, Maikona, Loiyangalani, Laisamis and Central—could each have a different index level. Because insurance payments are made according to the index level, this means that IBLI may make different indemnity payments across divisions. Every insurance policy holder within the same division, however, will receive the same rate of insurance payment, provided that the index is above the strike.

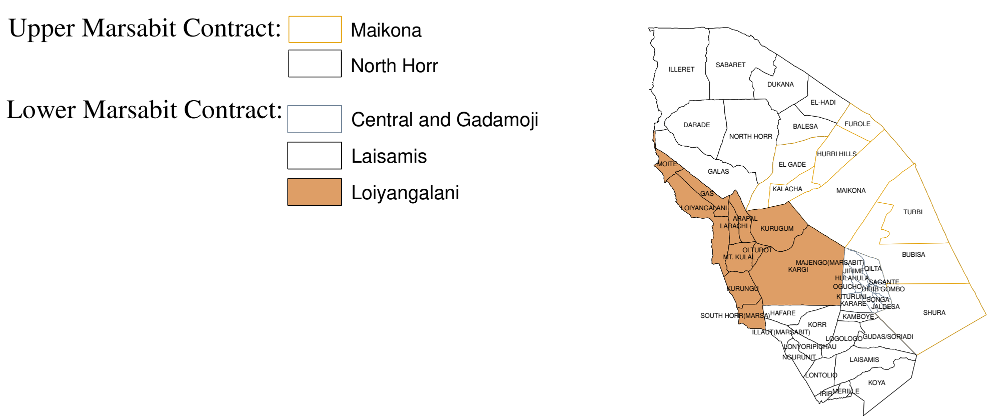

Figure A1. *IBLI Geographical Coverage*

Contract premium rates and indemnity payments:

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

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

There are no indemnity payments if the index falls below the strike (15%). If the index exceeds the strike, indemnity payments are calculated as the product of the value of the insured herd and difference between the predicted livestock mortality and the deductible.

Time Coverage of IBLI:

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

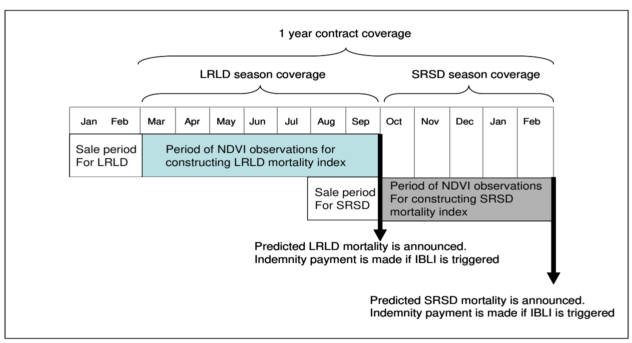

Figure A2. *Temporal Structure of IBLI Contract*

Appendix B. Description of the Key Variables and Analysis of Attrition

The data used in this research was collected by the IBLI field team in Marsabit, Kenya. The data was collected in four annual survey rounds in October and November. The 16 sublocations included in the survey were selected intentionally to represent a wide range of market and ecological conditions. Proportional sampling was done at the community level and stratified random sampling was done within communities. The survey tool included a wide variety of questions on household's demographic and economic characteristics. It emphasizes livestock related data, such as herd composition and detailed monthly livestock intake and offtake. The variable construction and summary statistics are found in Tables B1 and B2.

Table B1

Description of Key Variables

Variable	Data Frequency	Description
Male	Annual	Sex of the head of household (1=male).
Age of Head	Annual	Age of the head of household (years).
Education	Annual	Maximum education level achieved within the household (years).
Risk Aversion	Constant	Following Binswanger (1980), households were allowed to choose from a menu of real gambles in which level of risk and expected outcome were positively correlated. Each household participated in the experiment once during their first survey round. Households are then placed into a risk aversion category according to the lottery that they choose. The categories are risk neutral, moderately risk averse, and extremely risk averse.
Dependency Ratio	Annual	Ratio of members that are younger than 15 years, older than 55 years, disabled, or clinically ill.
Social Groups	Annual	A count of the number of informal groups in which the household participates. This variable is lagged by one period in the analysis.
Asset Index	Annual	The asset index is generated by a factor analysis performed on more than 30 variables capturing asset ownership from the following categories: productive assets, household construction materials, household facilities, cooking and lighting fuels, and consumer durables. This variable is lagged by one period in the analysis.
Ln income	Seasonal	Ln(1+ average monthly income) where income is the sum of the value of earnings, milk production, livestock slaughter, and livestock sales. Earnings include earnings from sale of crops, salaried employment, pensions, casual labor, business, petty trading, gifts, and remittances, expressed in Kenyan shillings (Ksh). This variable is lagged by one period.
Ratio Livestock Income	Seasonal	Ratio of income that is generated through milk production, livestock slaughter or livestock sales. This variable is lagged by one period in the analysis.
Herd Size	Seasonal	Average herd size during the sales window (1 TLU=0.7 camels=1 cattle=10 sheep=10 goats). This variable is lagged by one period in the analysis.
Livestock Mortality Rate	Seasonal	Seasonal livestock mortality rate is calculated by dividing total losses within a season by the total herd owned within that season. Total herd owned is the sum of beginning herd size and all additions to the herd during the season. This variable is lagged by one period in the analysis.
Risk	Constant	Within household variance in livestock mortality rate from the three periods before IBLI was introduced.
Savings	Annual	A dummy variable that is equal to one if the household has cash savings sufficient to purchase IBLI insurance for ten TLUs. Savings are estimated by summing the total monies held at home, in merry-go-round groups, in micro-finance institutions, in savings and credit cooperatives, in bank accounts, with traders or shops, and in M-Pesa (a mobile-based micro-finance institution) accounts. This variable is lagged by one period in the analysis.
HSNP	Seasonal	Participation in HSNP (1=participant). This variable is lagged by one period.
HNSP Eligible	Seasonal	HSNP transfers are currently being made in the household's community and the household meets the eligibility criteria for its community. See Jensen, Barrett, and Mude (2016) for more information on the intent to treat variable.
HSNP Community	Seasonal	Community is an HSNP target community (1=target community).
Expected Rangeland: Good/Normal/Poor	Annual	A set of three dummy variables reflecting that the respondent's prediction of coming season's rangeland conditions were: much above normal or above normal (Good=1), normal (Normal=1), or somewhat below normal or much below normal (Poor=1).

(Table continues)

(Continued)

Ln(Effective Price)	Seasonal	Log of the price for one TLU of coverage after coupon discounts (ln(Ksh)).
Basis Risk	Seasonal	The mean of squared observed underpayments.
IBLI game	Constant	Household participated in the IBLI educational game in 2010 (1=participant).
Coupon	Seasonal	Household received a discount coupon (1=true).
Pre-Czndvi	Seasonal	Preceding season's cumulative standardized normalized difference vegetation index.

Table B2 provides summary statistics of the key variables, distinguishing between those that purchase and those that do not purchase IBLI. There seem to be a number of significant differences between those that do purchase IBLI and those that do not.

Table B2

Summary Statistics

	Never Purchase (N=450)		Did Purchase (N=382)				
Variable	Mean	Std. Err.	Mean	Std. Err.	Difference	t-stat	
Male	0.57	0.02	0.62	0.02	0.05	2.27	**
Age	47.8	0.55	47.8	0.55	0.06	0.07	
Education	4.14	0.14	4.56	0.16	0.42	2.04	**
Dependency Ratio	0.62	0.01	0.60	0.01	-0.02	-1.91	*
Social Groups	0.55	0.02	0.77	0.03	0.21	5.67	***
Income	7,343	260	7,598	371	255	0.56	
Ratio Livestock Income	0.65	0.01	0.66	0.01	0.01	0.43	
Herd Size	12.0	0.56	12.3	0.61	0.34	0.42	
Asset Index	-0.10	0.03	0.04	0.03	0.14	3.32	***
Savings	0.09	0.01	0.12	0.01	0.03	2.13	**
HSNP	0.36	0.01	0.29	0.02	-0.07	-3.00	***
HSNP Eligible	0.35	0.01	0.24	0.01	-0.12	-5.84	***
HSNP Community	0.61	0.02	0.50	0.02	-0.11	-4.58	***
Risk Aversion: Neutral	0.27	0.01	0.28	0.02	0.01	0.58	
Risk Aversion: Moderate	0.39	0.02	0.47	0.02	0.08	3.34	***
Risk Aversion: Extreme	0.34	0.02	0.25	0.02	-0.09	-4.18	***
Risk (x100)	7.09	0.38	5.89	0.29	-1.19	-2.49	**
Basis Risk (x100)	5.00	0.30	4.05	0.27	-0.95	-2.33	**
Subsidy	-0.52	0.01	-0.49	0.01	0.03	3.63	***
IBLI Game	0.28	0.01	0.34	0.02	0.06	2.67	***
Expected Rangeland Conditions: Good	-0.04	0.01	-0.04	0.01	0.00	0.07	
Expected Rangeland Conditions: Bad	0.02	0.01	0.00	0.01	-0.02	-1.46	
Pre-Czndvi	-5.62	0.30	-5.79	0.32	-0.16	-0.37	
Division Average Losses (x100)	15.21	0.05	15.37	0.05	0.16	2.10	**
Division Average Basis Risk (x100)	4.73	0.11	4.79	0.12	0.00	0.39	
Coupon	0.56	0.02	0.66	0.02	0.10	4.30	***

Notes: This table only includes the 832 balanced panel households in order to correctly categorize the "Never Purchase" households and maintain consistency in the periods and shocks captured in the summary statistics. *** p<0.01, ** p<0.05, * p<0.1. *Source:* Authors' calculations.

The asset index is constructed by performing a factor analysis on a set of variables meant to capture variation in household wealth. This approach is discussed in Sahn and Stifle (2000). The variables focus on five general categories: household construction materials, household facilities, cooking and lighting fuels, and household durables. Because the list of possible durables is extremely long (more than 70), they are aggregated by value (small, medium, large) and use (productive, other) except for large assets which are divided into those with motors and those without. Categorization was performed by the authors and is clearly not the only method for dividing or aggregating the long list of assets. When in doubt as to which category to place an item, we relied on the frequency of ownership to guild our decision. Table B3 includes the descriptions of each variable and the factor loadings, which were estimated using the variables listed and division year fixed effects.

Table B3
Asset Index

Variable	Description	Factor Loading
Improved Wall	=1 if walls are stone, brick, cement, corrugated iron, mud plastered with cement, or tin	0.132
Improved Floor	=1 if floor is cement, tile, or wood	0.130
Improved Toilet	=1 if toilet is flush or covered latrine	0.128
Improved Light	=1 if main source of lighting is electricity, gas, solar	0.118
Improved cooking appliance	=1 if main cooking appliance is jiko, kerosene stove, gas cooker, or electric cooker	0.077
Improved Fuel	=1 if main cooking fuel is electricity, paraffin, gas or charcoal	0.064
Improved furniture	Total number of the following assets: metal trunks, mosquito nets, modern chairs, modern tables, wardrobes, mattresses and modern beds	0.165
Water Source: Open	=1 if main water source is river, lake, pond, unprotected well or unprotected spring	0.004
Water Source: Protected	=1 if main water source is protected spring or protected well	0.004
Water Source: Borehole	=1 if main water source is a borehole	-0.008
Water source: Tap	=1 if main water source is a public or private tap	0.040
Water Source: Rainwater catchment	=1 if main water source is a rainwater catchment (usually cement or plastic)	0.079
Water Source: tanker	=1 if main water source is water tanker (usually associated with NGO and food aid activities during drought)	0.021
Education	Maximum household education	0.121
Total cash savings	Total monies held at home, in merry-go-round groups, in micro-finance institutions, in savings and credit cooperatives, in bank accounts, with traders or shops, and in M-Pesa (a mobile-based micro-finance institution) accounts.	0.085
Land	Hectares owned	0.051
Irrigation	=1 if household owns irrigated land	0.033
Poultry	Number of chickens	0.081
Donkeys	Number of donkeys	0.018
Very small	Total number of the following assets: gourds, cups, scissors, and needle and thread sets.	0.040
Small tools	Total number of the following assets: anvils, panier, sickle, pickaxe, hoe, spade, machetes, spears, bows, club, chisels, hammers, files, fishing lines.	0.126
Small other	Total number of the following assets: musical instruments, traditional tools, bells, knifes, basins, sufirias, thermoses, buckets, wristwatches, jewelry	0.053
Medium tools	Total number of the following assets: Wheelbarrows, fishing nets, mobile phones, washing machines, spinning machines, weaving machines, sewing machines, bicycles, and plows.	0.164
Medium other	Total number of the following assets: water tank, jerry can, paraffin lamp, water drum, kerosene stove, charcoal stoves, ovens and radios.	0.135
Large	Total number of the following assets: animal carts, shops, stalls and boats.	0.037
Large with motor	Total number of the following assets: cars, motorbikes and tractors.	0.089

Notes: Division*period dummies included in the factor analysis.

Attrition rates averaged about 4% per year and the rate of attrition was similar between survey rounds. Table B4 provides details on the differences between full balanced panel households and those that left. Note that HSNP transfers, HSNP eligibility, participation in the IBLI extension game, the subsidy, (observed) basis risk, discount coupon, and expected conditions are all related to time so that we expect there to be systematic differences in those variables between those whom we observe in all periods and those that exit, due purely to exogenous factors. Those characteristics aside, there do seem to be differences in education, dependency ratio, social groups, dependence on livestock, and assets between those that are in the full panel and those that entered/left.

Table B4

Summary Statistics for Those that Stayed and Those that Left/Entered the Survey

	Full Panel (N=832)		Left/Entered (N=94)			
Variable	Mean	Std. Err.	Mean	Std. Err.	Difference	t-stat
Male	0.59	0.02	0.63	0.05	0.04	0.83
Age	47.5	0.76	47.6	1.38	0.13	0.08
Education	4.15	0.20	2.78	0.39	-1.37	-3.17 ***
Dependency Ratio	0.62	0.01	0.56	0.02	-0.05	-2.34 **
Social Groups	0.60	0.03	0.45	0.05	-0.15	-2.48 **
Income	7,371	374	7,006	817	-366	-0.41
Ratio Livestock Income	0.7	0.02	0.5	0.05	-0.11	-2.22 **
Herd Size	14.1	0.71	13.5	1.67	-0.58	-0.32
Asset Index	-0.06	0.04	-0.30	0.06	-0.24	-3.30 ***
Savings	0.10	0.01	0.13	0.03	0.03	0.79
HSNP	0.24	0.01	0.17	0.03	-0.07	-2.19 **
HSNP Eligible	0.23	0.02	0.07	0.02	-0.16	-6.02 ***
HSNP Community	0.56	0.02	0.53	0.05	-0.03	-0.54
Risk Aversion: Neutral	0.27	0.02	0.34	0.05	0.07	1.36
Risk Aversion: Moderate	0.43	0.02	0.40	0.05	-0.02	-0.45
Risk Aversion: Extreme	0.30	0.02	0.26	0.04	-0.04	-0.92
Risk (x100)	6.64	0.51	9.84	2.00	3.20	1.55
Basis Risk (x100)	2.99	0.21	1.49	0.31	-1.50	-4.02 ***
Subsidy	-0.60	0.00	-0.65	0.01	-0.04	-4.83 ***
IBLI Game	0.30	0.02	0.16	0.04	-0.15	-3.40 ***
Expected Rangeland Conditions: Good	0.21	0.01	0.12	0.02	-0.09	-4.72 ***
Expected Rangeland Conditions: Bad	0.40	0.01	0.20	0.02	-0.20	-8.55 ***
Pre-Czndvi	-2.91	0.07	-2.22	0.54	0.69	1.28
Division Average Losses (x100)	15.28	0.07	14.99	0.18	-0.28	-1.46
Division Average Basis Risk	3.20	0.04	3.20	0.29	0.00	0.01
Coupon	0.60	0.01	0.37	0.04	-0.23	-5.44 ***

Notes: *** p<0.01, ** p<0.05, * p<0.1.

The survey teams used a census of households with herd sizes in order to replace exit households with households from the same wealth stratum. Thus we expect that the exiting and replacement households are similar. Descriptive statistics are found in Table B5. Most of the systematic differences are likely due to duration of survey participation and likelihood of participating during certain periods rather than actual differences between households. Omitting those explicitly tied to time, the differences that are most worrisome are herd size and ratio of income from livestock, which indicate that replacement households have much smaller herds and are more dependent on those herds than those that left. This is most likely a result of over-sampling in the wealthy household strata, which leaves fewer eligible replacements for attrited wealthy households, which means that less wealthy households often replaced those that left from the wealth strata.[31]

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

Table B5

Summary Statistics for Entry Vs. Exit Households

	Exit (N=91)		Enter (N=91)			
Variable	Mean	Std. Err.	Mean	Std. Err.	Difference	t-stat
Male	0.62	0.07	0.64	0.07	0.02	0.17
Age	47.4	1.95	47.8	1.95	0.43	0.15
Education	3.43	0.54	2.19	0.56	-1.25	-1.60
Dependency Ratio	0.59	0.03	0.54	0.03	-0.04	-1.03
Social Groups	0.40	0.08	0.50	0.07	0.09	0.85
Income	5,901	1,074	8,017	1,207	2,116	1.31
Ratio Livestock Income	0.37	0.05	0.71	0.06	0.34	4.21 ***
Herd Size	18.6	3.10	8.8	1.20	-9.78	-2.94 ***
Asset Index	-0.30	0.07	-0.31	0.10	0.00	-0.04
Savings	0.09	0.04	0.15	0.05	0.06	1.04
HSNP	0.12	0.04	0.22	0.04	0.11	1.99
HSNP Eligible	0.06	0.02	0.27	0.10	0.21	2.12 *
HSNP Community	0.51	0.07	0.55	0.07	0.04	0.36
Risk Aversion: Neutral	0.28	0.06	0.40	0.07	0.12	1.31
Risk Aversion: Moderate	0.40	0.07	0.41	0.07	0.01	0.13
Risk Aversion: Extreme	0.32	0.07	0.19	0.05	-0.13	-1.56
Risk (x100)	10.06	2.08	4.23	2.14	-5.83	-1.96 *
Basis Risk (x100)	0.33	0.13	2.54	0.56	2.21	3.86 ***
Subsidy	-0.67	0.01	-0.63	0.01	0.04	2.48 **
IBLI Game	0.32	0.07	0.00	0.00	-0.32	-4.70 ***
Expected Rangeland Conditions: Good	0.12	0.02	0.11	0.02	-0.01	-0.36
Expected Rangeland Conditions: Bad	0.22	0.03	0.18	0.02	-0.04	-1.12
Pre-Czndvi	-5.70	0.36	0.97	0.74	6.67	8.10 ***
Division Average Losses (x100)	15.05	0.27	14.94	0.24	-0.11	-0.31
Division Average Basis Risk	1.01	0.17	5.21	0.28	4.20	12.98 ***
Coupon	0.62	0.08	0.24	0.03	-0.38	-4.23 ***

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Appendix C: Balancing Tables for IBLI Coupon and IBLI Educational Game

The period examined by this research included four sales periods, and thus four rounds of random discount coupons distribution. By the fourth round, most households had received a discount coupon at least once and many had received more than one (Table C1).

Table C1

Distribution of Coupons by the Final Survey Round

Number of discounts received	Frequency
0	139
1	326
2	203
3	135
4	29

As a check of balance for the coupons, we create a two treatment intensity variables (1) the number of coupons received, and (2) the sum of the percent discounts received. Those two variables are then separately regressed onto the baseline values of the set of covariates used in the main regression (Table C2). If certain types of households were favored or penalized by the randomization, it will be apparent in statistically significant coefficient estimates in the regressions. We use the balanced panel for this regression so that we do not conflate the impact of shorter panels with unbalanced treatments. Of the fifteen coefficient estimates examined, two, ratio of income from livestock and savings, show statistical evidence of unbalance. Randomization favored those that rely more on livestock for their income and those with more savings. The rate of coefficient estimates that are statistically different at the 10% level is 13%, 3% higher than expected but still quite close. As a precaution, we are sure to control for ratio of income from livestock and savings in all of our analysis.

We also check for balance across the IBLI extension game. The extension game was implemented by randomly selecting about half of the households from a random selection of 9 of the 16 sublocations. See McPeak, Chantarat, and Mude (2010) for more information on implementation. We check for balance across households within those 9 communities in which the game was played (Table C3). There are very few differences, although the sub-sample of participants are more likely to be extremely risk averse than their non-participant counterparts. We have no hypothesis as to why that may be but are sure to control for level of risk aversion in all of our analysis.

Table C.2

Balance Check for Coupon Distribution: Coefficient Estimates from Regressing Characteristics onto Coupon Status

VARIABLES	(1) Count of Discount Coupons	(2) Sum of Discounts Received
Head is Male	-0.0127	0.0366
	(0.0998)	(0.0408)
Age of Head	0.0025	0.0008
	(0.0025)	(0.0012)
Maximum Education in the Household	0.0024	-0.0055
	(0.0120)	(0.0054)
Dependency Ratio	-0.1617	-0.0291
	(0.2405)	(0.1046)
Social Groups	-0.0340	-0.0146
	(0.0550)	(0.0252)
Income (1,000 KSH)	0.0000	0.0000
	(0.0000)	(0.0000)
Ratio Income Livestock	0.2271**	0.0944**
	(0.1029)	(0.0445)
TLU	-0.0010	-0.0004
	(0.0018)	(0.0008)
Asset Index	-0.0147	-0.0052
	(0.0591)	(0.0262)
Savings (10 TLU)	0.4640**	0.2506**
	(0.1871)	(0.0998)
Will be HSNP participant	0.0675	0.0010
	(0.1206)	(0.0516)
HSNP Sublocaiton	0.0877	0.0357
	(0.1167)	(0.0547)
Risk Aversion: Moderate	0.0562	0.0392
	(0.1012)	(0.0464)
Risk Aversion: Extreme	0.1095	0.0228
	(0.1222)	(0.0517)
Participated in IBLI Extension Game	0.0750	0.0484
	(0.1038)	(0.0471)
Constant	1.9874***	0.6513***
	(0.2453)	(0.1083)
Observations	772	772
R-squared	0.0464	0.0422

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Table C.3

Balance Check for the Randomized Game Participation within Treated Sublocations

	Did Not Play IBLI Game (N=302)		Played IBLI Extension Game (N=275)				
VARIABLES	Mean	Std. Err.	Mean	Std. Err.	Difference	t-stat	
Head is Male	0.49	0.04	0.57	0.04	0.09	1.50	
Age of Head	44.2	1.29	47.5	1.53	3.38	1.69	*
Maximum Education in the Household	3.16	0.31	3.07	0.29	-0.09	-0.20	
Dependency Ratio	0.63	0.02	0.62	0.02	-0.01	-0.43	
Social Groups	0.40	0.06	0.45	0.06	0.05	0.60	
Income (1,000 KSH)	4,505	498	3,872	477	-633	-0.92	
Ratio Income Livestock	0.49	0.04	0.50	0.04	0.01	0.21	
TLU	19.8	2.06	18.9	2.54	-0.85	-0.26	
Asset Index	-0.25	0.05	-0.27	0.05	-0.02	-0.31	
Savings (10 TLU)	0.06	0.02	0.06	0.02	0.00	-0.12	
Will be HSNP participant	0.33	0.04	0.32	0.04	-0.01	-0.15	
HSNP Sublocation	0.48	0.04	0.47	0.04	-0.01	-0.14	
Risk Aversion: Extreme	0.26	0.04	0.44	0.04	0.18	3.27	***

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Appendix D. Coefficient Estimates and AME of Demand from a Pooled Model

Table D1

Coefficient Estimates on Demand for IBLI (Pooled Model)

	Uptake		Level (TLU)	
VARIABLES	Coefficient	Std. Err.	Coefficient	Std. Err.
Household Period-Specific Characteristics:				
Male [A]	0.0870	(0.0865)	0.1698**	(0.0830)
Age [A]	-0.0079*	(0.0046)	-0.0109**	(0.0043)
Age^{2} [A]	-0.0001	(0.0003)	-0.0000	(0.0003)
Education [A]	0.0050	(0.0442)	0.0103	(0.0454)
Dependency Ratio [A]	0.7030**	(0.3300)	0.6509*	(0.3746)
Social Groups [A]	0.0140	(0.0620)	0.0216	(0.0521)
Ln(income) [A]	0.0119	(0.0262)	0.0139	(0.0266)
Ln(income)^{2} [A]	0.0047	(0.0045)	-0.0025	(0.0044)
Ratio income livestock [A]	-0.1345	(0.1339)	-0.2688**	(0.1358)
TLU [A]	0.0066*	(0.0040)	0.0118***	(0.0038)
TLU^{2} [A]	-0.0002	(0.0001)	-0.0002	(0.0001)
Asset Index	-0.1276	(0.1194)	-0.0933	(0.0981)
Savings (10TLU) [A]	-0.3079	(0.1909)	-0.2135	(0.1932)
HSNP [A]	0.2709	(0.1681)	0.3140**	(0.1325)
HSNP Eligible [A]	0.0556	(0.1904)	-0.0852	(0.1876)
HSNP Village	-0.1362*	(0.0827)	-0.0737	(0.0891)
Moderately Risk Averse	-0.0367	(0.0956)	-0.0333	(0.0905)
Extremely Risk Averse	-0.2438**	(0.1058)	-0.1383	(0.0936)
Risk	-0.9276**	(0.4535)	-0.5728	(0.4718)
Discount Coupon (=1 if recipient)	0.2772***	(0.0886)		
Hypothesis 1: Basis Risk And Price				
Basis Risk	-1.2360	(1.2806)	-0.5496	(1.1530)
Ln (Subsidy)	1.0502***	(0.2766)	1.3861***	(0.2158)
Basis Risk x Ln (Subsidy)	-1.9820	(2.1852)	-0.3184	(2.0074)
Hypothesis 2: Basis Risk And Learning				
Game	0.2651**	(0.1170)	0.2129**	(0.0988)
Basis Risk X Game	-3.1822**	(1.2815)	-2.0098*	(1.1015)
Hypothesis 3: Intertemporal Adverse Selection				
Expected Conditions: Good=1 [B]	-0.0977	(0.0951)	-0.0882	(0.0852)
Expected Conditions: Bad=1 [B]	-0.2417**	(0.1044)	-0.2435**	(0.1110)
Pre-CZNDVI	-0.0091**	(0.0046)	-0.0071	(0.0053)
Hypothesis 4: Spatial Adverse Selection				
Division Average Loss Rate	3.8613	(2.4541)	1.4348	(2.3456)
Division Average Basis Risk	-4.2090**	(1.8857)	-1.3583	(1.7809)
Division Average Basis Risk X Game	-1.2328	(2.5023)	-3.2869	(2.1188)
Observations				3,096
Wald test of Independent Equations χ^2				160.35
Model Wald χ^2				146.80

Notes: Additional covariates not listed above include time dummies and a constant. [A] Variable is demeaned and lagged one period. [B] Variable is demeaned. [#]Omitted variable is E*xpected conditions: poor*. Household clustered and robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table D2

Average Marginal Effects (AME) on Demand for IBLI (Pooled Model)

	Uptake		Level (TLU)	
VARIABLES	AME	Std. Err.	AME	Std. Err.
Household Period-Specific Characteristics:				
Male [A]	0.0198	(0.0196)	0.1698**	(0.0830)
Age [A]	-0.0018*	(0.0010)	-0.0109**	(0.0044)
Education [A]	0.0011	(0.0101)	0.0103	(0.0454)
Dependency Ratio [A]	0.1601**	(0.0760)	0.6509*	(0.3746)
Social Groups [A]	0.0032	(0.0141)	0.0216	(0.0521)
Ln(income) [A]	0.0031	(0.0063)	0.0121	(0.0287)
Ratio income livestock [A]	-0.0306	(0.0303)	-0.2688**	(0.1358)
TLU [A]	0.0016*	(0.0009)	0.0127***	(0.0040)
Asset Index [A]	-0.0291	(0.0271)	-0.0933	(0.0981)
Savings (10TLU) [A]	-0.0701	(0.0435)	-0.2135	(0.1932)
HSNP [A]	0.0617	(0.0382)	0.3140**	(0.1325)
HSNP Eligible [A]	0.0127	(0.0434)	-0.0852	(0.1876)
HSNP Village	-0.0310*	(0.0188)	-0.0737	(0.0891)
Moderately Risk Averse	-0.0084	(0.0217)	-0.0333	(0.0905)
Extremely Risk Averse	-0.0555**	(0.0239)	-0.1383	(0.0936)
Risk	-0.2113**	(0.1032)	-0.5728	(0.4718)
Discount Coupon (=1 if recipient)	0.0631***	(0.0202)		
Hypothesis 1: Basis Risk And Price				
Basis Risk	-0.2924**	(0.1244)	-0.9814**	(0.4583)
Ln (Subsidy)	0.2230***	(0.0588)	1.3716***	(0.1893)
Hypothesis 2: Basis Risk And Learning				
Game	0.0265	(0.0200)	-0.0243	(0.0745)
Hypothesis 3: Intertemporal Adverse Selection				
Expected Conditions: Good=1 [B, C]	-0.0222	(0.0217)	-0.0882	(0.0852)
Expected Conditions: Bad=1 [B, C]	-0.0550**	(0.0239)	-0.2435**	(0.1110)
Pre-CZNDVI	-0.0021**	(0.0010)	-0.0071	(0.0053)
Hypothesis 4: Spatial Adverse Selection				
Division Average Loss Rate	0.8794	(0.5599)	1.4348	(2.3456)
Division Average Basis Risk	-1.0437***	(0.3746)	-2.3292	(1.5562)
Observations				3,096
Wald Test of Independent Equations χ^2				177.45
Model Wald χ^2				146.80

Notes: Additional covariates not listed above include time dummies and a constant. [A] Variable is demeaned and lagged one period. [B] Omitted variable is E*xpected conditions: normal*. [C] Variable is demeaned. Household clustered and robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Appendix E: Shapley Goodness of Fit Decomposition

A Shapley's goodness of fit (GOF) decomposition is used to determine the level of variation in demand that is captured by categories of variables (Kolenikov & Shorrocks 2005; Shapley 1953; Shorrocks 2013).[32] The variable categories include: household demographics, household finances, price, basis risk and knowledge, prospective intertemporal adverse selection, and prospective spatial adverse selection and the instrument variable/inverse Mills ratio. A two-stage Heckman approach, rather than the maximum likelihood approach used in the main body of the paper, is used here in order to examine the contributions of the variable groups in both the uptake and demand analysis.

Tables E1 and E2 include the two-stage estimates and estimated group contributions to each stage's (uptake and level of purchase) GOF. The maximum likelihood estimates from the Heckman selection model (from Table 6) are also included as evidence that the two models result in very similar estimates and that the decomposition of the two-stage estimates are likely to be reflective of the contributions in the maximum likelihood Heckman model.[33]

Household characteristics clearly play a role in uptake but are unable to account for even half of the variation captured by the model (Table E1 and Table E2). The subsidy alone provides about 10% of the GOF of our model for both uptake and level. Basis risk and knowledge are nearly as important in the uptake decision as the subsidy, but their importance falls for the coverage decision. Temporal and spatial adverse selection provide similar contributions and their combined impacts are larger than the basis risk and knowledge group, illustrating the importance of this rarely examined component of demand for index insurance.

In summary, the total contribution made by basis risk, knowledge of the product, and adverse selection towards the GOF are on par with the importance of price in our model. Our models would perform much worse with these crucial estimates of basis risk and adverse selection.

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

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

Table E1

Decomposition of Pseudo R^2 for Uptake Probit

VARIABLES	Heckman ML Probit Coefficient	Heckman ML Probit Std. Err.	2 Step Probit Coefficient	2 Step Probit Std. Err.	Shapley Decomposition of Pseudo R^2 [A]
Household Specific Characteristics:					
Demographics:					29.93%
Male [A]	0.0226	(0.0907)	0.0271	(0.1015)	
Age [A]	-0.0080*	(0.0048)	-0.0079	(0.0055)	
Age^2 [A]	0.0000	(0.0002)	0.0001	(0.0002)	
Education [A]	0.0147	(0.0432)	0.0071	(0.0529)	
Dependency Ratio [A]	0.7795**	(0.3335)	0.7717**	(0.3515)	
Social Groups [A]	0.0494	(0.0553)	0.0391	(0.0599)	
HSNP Eligible	0.1037	(0.1980)	0.0798	(0.2092)	
HSNP Village	0.0673	(0.1201)	-0.0073	(0.1244)	
Moderately Risk Averse	-0.0444	(0.0931)	-0.0282	(0.0998)	
Extremely Risk Averse	-0.1902*	(0.1040)	-0.2196*	(0.1137)	
Risk	-0.8503*	(0.5083)	-0.8242	(0.5585)	
Financial:					17.95%
Ln(income) [A]	0.0348	(0.0285)	0.0347	(0.0302)	
$Ln(income)^2$ [A]	0.0095**	(0.0047)	0.0125**	(0.0052)	
Ratio income livestock [A]	-0.1600	(0.1404)	-0.1429	(0.1478)	
TLU [A]	0.0061	(0.0041)	0.0045	(0.0043)	
TLU^2 [A]	-0.0002	(0.0001)	-0.0002	(0.0001)	
Asset Index	-0.1805*	(0.1039)	-0.1914	(0.1225)	
Savings (10TLU) [A]	-0.3485**	(0.1717)	-0.2482	(0.1866)	
HSNP [A]	0.3207*	(0.1722)	0.3024	(0.1890)	
Subsidy:	0.9684***	(0.2881)	0.2176	(0.3596)	10.94%
Basis Risk And IBLI Knowledge					9.13%
Basis Risk	-0.9527	(1.2988)	-0.7069	(1.3772)	
Basis Risk x Ln (Subsidy)	-1.8647	(2.1765)	-1.2634	(2.3712)	
Game	0.3024***	(0.1160)	0.3073**	(0.1266)	
Basis Risk X Game	-2.6114**	(1.2046)	-2.7586**	(1.3082)	
Intertemporal Adverse Selection					5.31%
Expected Conditions: Good=1 [B]	-0.0825	(0.0979)	-0.0742	(0.1029)	
Expected Conditions: Bad=1 [B]	-0.2477**	(0.1035)	-0.2991***	(0.1062)	
Pre-CZNDVI	-0.0085*	(0.0046)	-0.0105**	(0.0048)	
Household Mean Expected Conditions:			0.1408	(0.1779)	
Good=1	0.0803	(0.1678)			
Household Mean Expected Conditions:			0.0279	(0.2082)	
Bad=1	-0.0136	(0.1898)			
Spatial Adverse Selection					4.78%
Division Average Loss Rate	5.6283**	(2.7645)	6.3534**	(3.0101)	
Division Average Basis Risk	-4.8524**	(1.9611)	-4.3827**	(2.0925)	
Division Average Basis Risk X Game	-2.2374	(2.5614)	-1.9889	(2.7500)	
Instrumental Variable:					21.95%
Discount Coupon (=1 if recipient)	0.2858***	(0.0883)	0.6509***	(0.1355)	
Observations	3,096		3,096		
Wald test of Independent Equations χ^2	177.45				
Model Wald χ^2	174.49		235.51		
Psuedo R^2			0.132		

Notes: [A] Variable is demeaned and lagged one period. The variable's within household mean is also included as a covariate in the same group, but is not display in the table. [B] Variable is demeaned. [#]Omitted variable is E*xpected conditions: poor*. Household clustered and robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table E2

Decomposition R^2 for Level of Coverage Purchased, Conditional on Purchasing

	Heckman ML Probit		2 Step Probit		Shapley Decomposition of Pseudo R^{2} [A]
VARIABLES	Coefficient	Std. Err.	Coefficient	Std. Err.	
Household Specific Characteristics:					
Demographics:					22.68%
Male [A]	0.0824	(0.0836)	0.1009*	(0.0582)	
Age [A]	-0.0069	(0.0048)	-0.0038	(0.0063)	
Age^2 [A]	0.0001	(0.0002)	-0.0000	(0.0003)	
Education [A]	0.0328	(0.0388)	0.0354	(0.0319)	
Dependency Ratio [A]	0.5702	(0.3535)	0.2802	(0.3209)	
Social Groups [A]	0.0278	(0.0486)	0.0157	(0.0424)	
HSNP Eligible	0.2681*	(0.1416)	0.0076	(0.1926)	
HSNP Village	-0.0348	(0.1324)	0.0433	(0.0736)	
Moderately Risk Averse	-0.0337	(0.0832)	-0.0166	(0.0590)	
Extremely Risk Averse	-0.1105	(0.0924)	-0.0142	(0.0754)	
Risk	-0.6441	(0.4690)	-0.2997	(0.3714)	
Financial:					14.70%
Ln(income) [A]	0.0322	(0.0249)	0.0207	(0.0183)	
$Ln(income)^2$ [A]	0.0053	(0.0040)	-0.0017	(0.0038)	
Ratio income livestock [A]	-0.2280*	(0.1331)	-0.2377***	(0.0910)	
TLU [A]	0.0088**	(0.0036)	0.0080**	(0.0034)	
TLU^2 [A]	-0.0001	(0.0001)	0.0000	(0.0001)	
Asset Index	-0.0510	(0.0801)	0.0349	(0.0686)	
Savings (10TLU) [A]	-0.1735	(0.1609)	-0.0499	(0.1187)	
HSNP [A]	0.2681*	(0.1416)	0.2056	(0.1349)	
Subsidy:	1.2544***	(0.2129)	0.7553***	(0.2357)	13.04%
Basis Risk And Knowledge:					4.62%
Basis Risk	-1.1880	(1.1407)	-1.4121	(1.1789)	
Basis Risk x Ln (Subsidy)	-1.6360	(1.9513)	-2.0493	(2.2882)	
Game	0.2161**	(0.0939)	0.0945	(0.0850)	
Basis Risk X Game	-1.4809	(1.0525)	-0.3405	(1.0352)	
Intertemporal Adverse Selection:					2.61%
Expected Conditions: Good=1 [B]	-0.1053	(0.0845)	-0.0803	(0.0710)	
Expected Conditions: Bad=1 [B]	-0.2514**	(0.0999)	-0.0368	(0.0929)	
Pre-CZNDVI	-0.0087*	(0.0046)	-0.0021	(0.0041)	
Household Mean Expected Conditions: Good=1	0.2127	(0.1431)	0.0810	(0.1146)	
Household Mean Expected Conditions: Bad=1	0.4579***	(0.1751)	0.3711***	(0.1163)	
Spatial Adverse Selection					4.05%
Division Average Loss Rate	3.9716	(2.6839)	0.2245	(1.9542)	
Division Average Basis Risk	-2.4986	(1.8095)	-0.6512	(1.5055)	
Division Average Basis Risk X Game	-3.6911*	(2.1707)	-3.4996**	(1.7533)	
Selection:					38.30%
Rho/Inverse Mills Ratio	0.9735***	(0.0107)	0.2123	(0.1662)	
Observations	3,096		3,096		
Wald test of Independent Equations χ^2	177.45				
Model Wald χ^2	174.49				
R^2					

Notes: [A] Variable is demeaned and lagged one period. The variable's within household mean is also included as a covariate in the same group, but is not display in the table. [B] Variable is demeaned. [#]Omitted variable is E*xpected conditions: poor*. Household clustered and robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

References

Jensen, Nathaniel D, Christopher B Barrett, and Andrew G Mude. 2016b. Index Insurance and Cash Transfers: A Comparative Analysis from Northern Kenya. Unpublished.

Juárez, F. 2014. shapely2. STATA user-written command.

Kolenikov, S., & Shorrocks, A. 2005. A decomposition analysis of regional poverty in Russia. *Review of Development Economics*, 9(1), 25-46.

McPeak, John, Sommarat Chantarat, Andrew G. Mude (2010). "Explaining Index Based Livestock Insurance to Pastoralists," *Agricultural Finance Review*, 70(3), 333 – 352.

Sahn, D. E., & Stifel, D. C. 2000. Poverty comparisons over time and across countries in Africa. *World development*, *28*(12), 2123-2155.

Shapley, Lloyd. 1953. A value for n-person games. In *Contributions to the Theory of Games*, edited by H. W. Kuhn and A. W. Tucker: Princeton University Press.

Shorrocks, Anthony F. 2013. Decomposition procedures for distributional analysis: a unified framework based on the Shapley value. *Journal of Economic Inequality,* 11 (1):1-28.