PRO-POOR RISK MANAGEMENT:
ESSAYS ON THE ECONOMICS OF INDEX-BASED RISK TRANSFER PRODUCTS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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August 2009

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Cornell University 2009

This dissertation explores innovations in index-based risk transfer products (IBRTPs) as a means to address an important insurance market failure that leaves many poor and vulnerable populations exposed to considerable uninsured risk. IBRTPs can address problems of covariate risk, asymmetric information and high transaction costs that have precluded the emergence of formal insurance market in low-income areas, where uninsured risk remains a leading cause of persistent poverty.

A brief introductory chapter situates this dissertation in the broader, emergent literature on IBRTPs. The second chapter explains how the strong relation between widespread human suffering and weather shocks creates an opportunity to develop famine indexed weather derivatives to finance improved emergency response to humanitarian crises.

The third chapter explains how these instruments might be designed and used by operational agencies for famine prevention in response to slow-onset disasters. It uses household data to develop a famine index based on child anthropometric data that is strongly related to rainfall variability and other exogenous measures that are reliably available at low cost; that index can be used to trigger payments to improve the timeliness and cost-effectiveness of humanitarian response.

The fourth chapter develops commercially viable index based livestock insurance (IBLI) to protect livestock assets for northern Kenyan pastoralists. The underlying herd mortality index is constructed off a statistical model that relates

longitudinal household-level herd mortality data to remotely sensed vegetation index data. The resulting index performs well out of sample. Pricing and risk exposure analysis also demonstrate the commercial potential of the product, which has been taken up by financial institutions in Kenya for marketing in early 2010.

The fifth chapter explores the household-level performance of IBLI. It uses simulations parameterized based on household panel data, risk preference estimates elicited in field experiments and remote sensing vegetation data to explore how well IBLI performs in preserving household wealth in this setting characterized by bifurcated livestock growth dynamics characteristic of poverty traps. Willingness to pay and aggregate demand for the contract are also estimated. This analysis shows that bifurcation in livestock herd dynamics leads to nonlinear insurance valuation regardless of risk preferences.

BIOGRAPHICAL SKETCH

Sommarat Chantarat was born in Songkhla, Thailand on May 8, 1980. Together with two younger brothers, she grew up in a loving and active home, in an academic environment, where her parents were both university professors, and on tennis courts with her Dad also as a professional coach.

Sommarat graduated from Thammasat University, Bangkok, Thailand, with a B.A. in Economics in 2001. She received the Shell Centenary Scholarship to study at the University of Cambridge, United Kingdom, where she received a Master of Philosophy degree in Economics in 2002. Her dissertation studies the theory and empirics of speculative attacks on the Thai Baht during the great Asian financial crisis of 1997, under supervision of Ajit Singh, Andrew Harvey and Chris Meissner. Her growing interest in the world of finance brought her to the University of Chicago, where she pursued a Master of Science degree in Financial Mathematics under the AT&T Leadership Award, and gradated in 2003.

In the fall of 2003, Sommarat began her Ph.D. program in the Graduate field of Economics at Cornell University, where she slowly developed a passion for the field of development economics. Awarded a Doctoral Dissertation Improvement Grant from the United States Agency for International Development (USAID) Borlaug Leadership Enhancement in Agriculture Program, she spent four months in Kenya as a graduate fellow at the International Livestock Research Institute (ILRI), Kenya, where she joined a collaborative research team in developing index insurance for pastoral areas of Northern Kenya. Upon completion of her Ph.D., Sommarat will continue to work with the team as a post-doctoral associate.

ACKNOWLEDGMENTS

I have depended upon invaluable acts of support, generosity and guidance throughout my progress at Cornell. But perhaps more importantly, I would like to start by thanking my advisor, Chris Barrett, who spent countless hours of his time and effort to share his knowledge, experience and care. I am especially thankful for his patience, encouragement and understanding. I owe my great appreciation to Calum Turvey and Andrew Mude especially for their expertise, optimism, leadership and support. The exceptional qualities of these three, who I consider mentors, co-authors, fathers and friends, allowed me to grow academically and socially. I also thank Kaushik Basu for serving in my Special Committee and for his encouragement and comments on the earlier versions of this work. I am grateful to Sharon Tennyson for her insightful comments and availability to serve as a proxy at my examination.

At Cornell, I was funded by a graduate teaching assistantship at the Department of Economics and research assistantships from the Global Livestock Collaborative Research Support Program, funded by the Office of Agriculture and Food Security, Global Bureau, USAID, under grant number DAN-1328-G-00-0046-00, through the Assets and Market Access Collaborative Research Support Program, and under grant number PCE-G-98-00036-00 through the Pastoral Risk Management Project. Various conference and travel grants were received from the Graduate School and the Institute for African Development of Cornell University, the Agricultural and Applied Economics Association Foundation and the European Association of Agricultural Economists. Their support was greatly appreciated.

Much of the inspiration, ideas and research support for this work were gained through fruitful brainstorming and collaboration within our Kenya index insurance research team. I would like to thank and share this achievement with my team members: Andrew Mude, Chris Barrett, Michael Carter, John McPeak, Munenobu Ikegarmi, Robert Ouma, Juliet Kariuki and Harriet Matsaert. I am especially grateful that this dissertation can offer an implementable opportunity as part of the team's efforts.

These dissertation chapters are also collaborative. The second, third and fifth chapters were co-authored with Chris Barrett, Calum Turvey and Andrew Mude, and the fourth chapter was co-authored with Andrew Mude, Chris Barrett and Michael Carter. I am indebted to all my co-authors for their remarkable contribution and understanding. This work also benefited greatly from suggestions and motivations provided by David Just, Ernst Berg, Martin Odening, Gary Fields, Ayago Wambile, Russell Toth and Felix Naschold. I greatly appreciate their time and encouragement.

My research and fieldwork in Kenya were made possible by support from the USAID Norman Borlaug Leadership Enhancement in Agriculture Program Doctoral Dissertation Improvement Grant, the World Bank Commodity Risk Management Program, the International Livestock Research Institute and the Graduate School of Cornell University. I thank them for this opportunity. Thanks are also due to the Kenya Agricultural Research Institute, Food for the Hungry and the Arid Land Resource Management Project for sharing their research, hospitality and logistical support throughout my stay in Marsabit district in northern Kenya. Special thanks are due to Robert Ouma for his exceptional expertise in fieldwork. I gained much of my field understanding from him. I am particularly indebted to my field enumerators: Waqo, Yara, Roba, Wata, Tesso, Judy, Ukure, Chris, Dae, Boru, Henry, James, Fabio, Gabriel and Korea for their exceptional work and friendship. I appreciated every bit of my experience with them. The pastoralists who participated in the household survey and experiments deserve acknowledgement for their cooperation and hospitality as well.

Most importantly, I dedicate my achievements to my family. Words are too limited to express my gratitude to them for their continuous love, support and encouragement. My strength and inspiration are devoted to my life-long best friend, Tavan Janvilisri, who is always there to witness my joys and disappointments. No step of my life would be pleasant and exciting without him around. Last but not least, I attribute my cheerfulness to my friends. Space is too scarce to write their countless names and my appreciation for their unconditional companionship.

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CHAPTER 1

INTRODUCTION

The central theme of development economics has always been how to eliminate poverty. Despite striking improvement in standards of living and a sharp fall in the global poverty rate over the past two or three decades, one third of the world still lives on $1.25 a day or less (Chen and Ravallion 2008). The problem is especially acute and persistent in sub-Saharan Africa. The persistence of extreme poverty, and its prevalence among particular groups defined by geography, caste, ethnicity or other attributes, has motivated widespread recent in "poverty traps" (Baulch and Hoddinott 2000; Sachs 2005; Barrett, Carter and Little 2007).

The economics literature has suggested several mechanisms by which poverty traps might emerge (Barrett and Swallow 2006; Bowles, Durlauf, and Hoff 2006; Carter and Barrett 2006; Azariadis and Stachurski 2007). Central to this literature is the hypothesized existence of multiple dynamic equilibria of well-being, at least one of which lies below a standard poverty line. Such settings are characterized by at least one critical threshold above which one is expected to be able to accumulate toward a satisfactory equilibrium standard of living, and below which one is expected to slide into a low-level poverty equilibrium. Various factors that seem to impede the poor's capacity to surmount the critical threshold all revolve around some combination of market imperfections that generate exclusionary mechanisms (e.g., credit and insurance rationing), resulting in the separation of subpopulations into distinct groups with different prospects.

This dissertation is motivated by the salience of uninsured risk as a common driver behind the existence of poverty traps, especially the covariate risk associated with extreme weather events – e.g., cyclones, droughts, floods, hurricanes, etc. – that devastate poor communities' productive assets with distressing frequency. Formal markets routinely fail to provide adequate insurance for such covariate risk in poor and infrastructure-deficit areas. And informal mutual insurance networks are structurally ill-suited to insure against covariate risk. This dissertation takes as its point of departure the importance of developing effective covariate risk management instruments as part of a strategy for reducing persistent poverty.

Weather-related disasters disproportionately affect the rural poor because their livelihoods tend to rely on agriculture, they have little self-insurance capacity, less reliable physical and institutional infrastructure to support external response, and weak access to credit or insurance for responding to shocks with financial instruments. Overall, people in low-income countries are four times more likely to die due to natural disasters (Gaiha and Thapa 2006). At the household level, evidence from drought in Ethiopia and Hurricane Mitch in Honduras indicates that poorer households feel the medium-term adverse effects more acutely and for a longer period than do better-off households (Carter et al. 2007). Furthermore, changing weather patterns appear likely to further increase the frequency and intensity of adverse weather events in the low-income tropics (Munich Re, 2006; IPCC 2007).

The combination of *ex post* losses due to adverse climate shocks and the likewise-substantial, albeit less-obvious opportunity cost of inefficient *ex ante* climate risk management likely play an important role in perpetuating extreme poverty. The most obvious mechanism is when adverse climate shocks knock a household beneath a critical threshold thereby setting them on a downward trajectory into destitution from which they do not recover (Dercon 1998; McPeak and Barrett 2001; Dercon 2005; Carter and Barrett 2006; Krishna 2006). People's response to shocks can likewise trap them in poverty. Poor households commonly liquidate assets to cope with the immediate consequence of shocks, which often drops people into irreversible destitution (Krishna 2006). Other poor households, recognizing the long-term risks of asset liquidation in the presence of poverty traps try to protect critical assets, which may require some combination of reduced food consumption, foregone health care, or withdrawal of children from school (Morduch 1995; Foster 1995; Zimmerman and Carter 2003; Barrett et al. 2006; Hoddinott 2006; Kazianga and Udry 2006). The resulting health and educational deficiencies can reduce human capital, further trapping the household in poverty intergenerationally (Jacoby and Skoufias 1997; Hoddinott and Kinsey 2001; Thomas et al. 2004; Dercon and Hoddinott 2005).

Recognizing these prospective consequences of shocks, people may go extraordinary lengths to manage risk exposure *ex ante*. The poor, who are generally more risk averse, generally appear more likely to select low-risk, low-return asset and livelihood strategies that reduce the risk of severe suffering but limit their growth potential, investment incentives and adoption of improved technologies (Feder, Just and Zilberman 1985; Eswaran and Kotwal 1989, 1990; Rosenzweig and Binswanger 1993; Morduch 1995; Bardhan, Bowles and Gintis 2000; Dercon 2005; Elbers et al. 2007). Such precautionary actions reinforce inherited patterns of chronic poverty. And because risk exposure leaves lenders vulnerable to default by borrowers, uninsured risk commonly limits access to credit, especially for the poor who lack collateral to guarantee loan repayment (Besley 1995). The combination of conservative portfolio choice induced by risk aversion that is strongly associated with poverty and credit market exclusion because risk exposure dampens lenders' willingness to lend helps perpetuate poverty.

A dearth of financial market instruments compounds the problems of ineffective and inefficient *ex ante* and *ex post* strategies to manage risk and cope with shocks, respectively. Of course, if financial markets permit people to insure against shocks *ex ante* or to borrow *ex pos*t so as to achieve quasi-insurance through *ex post* loan repayment, these adverse effects of risk should be attenuated or eliminated and risk need not contribute to the existence of poverty traps. Unfortunately, credit and insurance are routinely undersupplied in low-income areas. Poor households often lack access to formal financial markets that can facilitate consumption smoothing.[1]

The main causes leading toward formal financial failures are covariate risk, asymmetric information, and high transaction costs. First, spatially-correlated catastrophic losses, e.g., from weather-related disasters, can exceed the reserves of an insurer or lender, leaving unsuspecting policyholders or depositors unprotected.[2] Second, the existence of asymmetric information problems tends to expose lenders/insurers with losses that exceed the projections used to establish lending and premium rates due to classical problems of adverse selection and moral hazard. Third, the transaction costs of financial contracting in rural areas are much higher than in urban areas due to limited transportation, communication, legal infrastructure (Binswanger and Rosenzweig 1986) and the necessary information systems to control adverse selection and moral hazard. These high lending costs, combined with the small scale of intended borrowing by poor households, naturally leads to credit rationing that excludes the poor in equilibrium (Carter 1988).

Due to the limited availability of formal financial markets, people tend to rely heavily on a wide variety of informal risk transfer mechanisms to smooth consumption in rural areas (Besley 1995). These mechanisms vary from socially-constructed reciprocity obligations within family, village, religious community, or occupation

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[1] While microfinance has shown significant promise in some settings, the success has been limited in rural areas and for farming activities that require longer-term loans than is customary for microfinance (Armendáriz and Morduch 2005).

[2] Such covariate risk exposure explains why crop insurance policies are generally available only in countries where governments take on much of the catastrophic risk exposure faced by insurers (Binswanger and Rosenzweig 1986; Miranda and Glauber 1997).

(Coate and Ravallion 1993; Townsend 1994, 1995; Grimard 1997; Fafchamps and Lund 2003) to semi-formal microfinance, rotating savings and credit, or state-contingent loan arrangements (Hoff and Stiglitz 1990; Udry 1994). These informal mechanisms, however, tend to fail in the presence of large covariate risks (Rosenzweig 1988; Rosenzweig and Binswanger 1993; Townsend 1994; Dercon 1996). There is also evidence that access to these informal mechanisms is positively related to existing wealth (Jalan and Ravallion 1999; Santos and Barrett 2006; Vanderpuye-Orgle and Barrett 2009).

The increasing recognition of the considerable uninsured covariate risk exposure faced by the poor and its reinforcing impact on persistent poverty have sparked considerable interest in and experimentation with index based risk transfer products (IBRTPs) as a market-based means to transfer covariate climate risk. IBRTPs are financial instruments that make payments based on realizations of an underlying – transparent and objectively measured – index. For IBRTPs to be useful in transferring risk, the keys are a well-defined spatiotemporal coverage and a well-established index that is highly correlated with the aggregate losses being transferred and based on data sources not easily manipulable by either the insured or the insurer.[3] IBRTPs can take on any number of forms including insurance policies, option contracts, catastrophic bonds, etc. IBRTPs with indices based on cumulative rainfall, temperature, area average yield, satellite imagery and others have recently been developed to address covariate losses, especially those caused by natural disasters in low-income countries. Target users range from micro-level, retail clients (nomadic herders, small farmers) to meso- and macro-level institutional clients (e.g., cooperatives, microfinance

[3] For example, an IBRTP that protects against crop losses would be based on an index that is presumed to be highly correlated with farm-level yields.

institutions, governments, humanitarian organizations). These experiences are recently reviewed by Barrett et al. (2008) and Skees and Collier (2008).[4]

By design, IBRTPs can obviate several of the problems that bedevil financial contracting in low-income rural areas and can thereby help reduce financial markets failures that contribute to persistent poverty. Since realizations of the index are exogenous to policyholders, IBRTPs are not subject to the asymmetric information problems that plague traditional financial products. Thus, moral hazard and adverse selection problems should be considerably less than with traditional insurance products. Transaction costs are also typically much lower since the financial service provider does not have to verify farm-level expected yields or conduct farm-level loss assessment. Lastly, properly securitizing climate risk into a well-defined index opens up possibilities to transfer major covariate risk from low-income countries to international reinsurance, weather and financial markets at commercially viable costs. Although these financial innovations alone cannot solve the problem of chronic poverty, IBRTPs open up a range of intriguing new possibilities (Barrett et al. 2008; Barnett et al. 2008).

Opportunities offered by IBRTPs, however, come at the cost of basis risk, which refers to the imperfect correlation between an insured's potential loss experience and the behavior of the underlying index on which the index insurance payout is based. A contract holder may experience the type of losses insured against but fail to receive a payout if the overall index is not triggered. Conversely, while the

[4] Perhaps the best known examples of IBRTPs implemented in developing countries are: rainfall insurance to protect Mexico's national natural disasters social fund, FONDEN, from catastrophic drought (Alderman and Haque 2007); area mortality-based livestock insurance for herders in Mongolia (Mahul and Skees 2007); rainfall insurance for protecting farmers and microfinance institutions from drought and flood in India (Hess 2003; Gine et al. 2007); rainfall insurance linked to input loans to groundnut and maize farmers in Malawi (Hess and Syroka 2005; Osgood et al. 2007); and drought insurance to protect the World Food Programme (WFP)'s exposure to drought in Ethiopia (WFP 2005). At least 20 distinct IBRTPs have also been developed or proposed in other developing countries as of today.

aggregate experience may result in a triggered contract, some insured individuals may not have experienced losses yet still receive payouts. Thus, if an IBRTP is to be effective, the underlying index must be highly correlated with the loss being transferred over a relatively large geographic area. There must exist sufficient high-quality historical data representing the risk faced by the target population in order to establish this correlation and to estimate the probability distribution of the index. Most of the IBRTPs developed to date rely on weather data or crop growth models due to the limited availability of spatially and temporally rich household data in the targeted rural areas. The link to households' direct experience of risk is necessarily of uncertain strength, which raises important questions about whether IBRTPs indeed effectively reduce the poor's uninsured risk exposure sufficiently to justify their cost and to alter the dynamics of poverty among target populations.

This dissertation offers novel advances in applying the now-familiar quantitative design of IBRTPs to rich household data in an environment know to be characterized by threshold-based poverty traps. Because risk is especially pernicious in such settings, IBRTPs would seem to hold unusual promise. The four main chapters develop innovative IBRTPs that build the necessary indexes off of longitudinal household data statistically fit to data remotely sensed from satellite-based platforms, and then test the performance of the resulting IBRTP contracts against other household-level panel data and by simulating household performance with and without IBRTPs based on those data and risk preference parameters estimated among the same population using field experiments.

The arid and semi-arid lands (ASAL) of northern Kenya are the geographic focus of this study. Increasingly frequent and severe drought is a pervasive hazard that routinely causes great loss of livestock, the main asset the three million pastoralist households in the region hold, and severe and widespread malnutrition. Past empirical studies consistently find strong evidence of poverty traps in this pastoral region manifests in the form of bifurcations in livestock accumulation (McPeak and Barrett 2001; Lybbert et al. 2004; Barrett et al. 2006). Indeed, Santos and Barrett (2007) find that uninsured drought risk is a fundamental cause of the existence of multiple equilibria and associated poverty traps in the region. The strong link between drought risk and persistent poverty makes northern Kenya an ideal setting for studying whether IBRTPs might be useful in combating poverty traps.

The following chapters focus in turn on two distinct, complementary types of IBRTPs. These target different clients aiming to reduce poverty among northern Kenyan pastoralists. The first two chapters focus on instruments that could enhance provision of emergency response by governments, donors or humanitarian organizations to avert famine. The last two chapters focus on retail-level instruments designed to insure the livestock-based wealth of pastoralists. Our emphasis of these instruments on asset risk management resolves an important mismatch in the current literature and practice, where most insurance instruments globally are for assets, yet most IBRTPs in developing countries are focused on insurance. Asset risk management instruments, on the other hand, complicate the problem relative to income risk management instruments, which further deviates our methodology in development and evaluation from the existing literature in many interesting and innovative aspects.

The second chapter, which appeared in the *American Journal of Agricultural Economics* (Vol. 89, No. 5, December 2007), introduces the idea that the strong relation between widespread human suffering and weather shocks creates important opportunities for IBRTPs to help humanitarian organizations and governments respond more promptly and cost-effectively to humanitarian crises caused by drought, which ultimately could protect lives as well as livelihoods of the affected populations.

It proposes a conceptual framework for famine indexed weather derivatives (FIWDs) – weather derivatives indexed to forecasts of prevalence and severity of child undernutrition – and shows how FIWDs can be designed and used to enhance effective emergency response to slow-onset disasters. Using historical data on rainfall, food aid deliveries and of the international humanitarian funding appeals process, this paper demonstrates the potential economic and humanitarian value of FIWDs as a financial tool for managing humanitarian organizations' drought risk.

The third chapter, which appeared in the *Agricultural Finance Review* (Vol. 68, No. 1, Spring 2008), develops the design details of the proposed FIWDs for the specific cases of famine index insurance and famine catastrophe bonds. The proposed framework is then applied empirically to northern Kenya using household survey data collected monthly in three of the country's poorest districts, where food aid is routine but unpopular with donors and recipients both as a highly imperfect means of coping with drought. The chapter's main innovation is to demonstrate how a parametric and objectively measured famine index that could trigger FIWD payments can be constructed based on the strong statistical relationship between child malnutrition and rainfall. It is also shows how the FIWD could be used to layer catastrophic famine risk, thereby creating a complement to existing financial facilities in a most cost effective way.

The fourth chapter describes a novel effort at developing a commercially viable index based livestock insurance (IBLI) to protect northern Kenyan pastoralists from considerable livestock asset risk. It describes in detail the design of an IBLI contract based on remotely sensed measures of vegetative cover on rangelands. Those data exhibit the properties one wants for an IBRTP: precise, objectively verifiable, available at low cost in near-real time, not manipulable by either party to the contract, and, most importantly, strongly correlated with herd mortality. The key innovation is to construct, for the first time, an IBRTP based on a predicted asset loss index conditional on the observed intensity of deviation of vegetation index from normal. The resulting index performs very well out of sample, both when tested against other household-level longitudinal herd mortality data from the same region and period, and when compared qualitatively with community level drought experiences over the past 27 years. The historical, remotely sensed data on rangeland vegetation are then used to price the IBLI contract and analyze the potential risk exposure of the underwriter. That analysis establishes the reinsurance potential of the IBLI contract in international markets. The chapter concludes by discussing a few key operational challenges for upcoming commercial implementation of the IBLI contract in northern Kenya.

By addressing the core covariate asset risk of the vulnerable pastoralists, IBLI could offer substantial economic and social returns in the pastoral communities of northern Kenya. To the extent that the likelihood of severe herd mortality induces ineffective behavior responses and so reduces incentives to invest in herds and related productive activities of the risk averse households, insuring livestock against catastrophic loss would address the high risk of investment in such environments. By thus stabilizing asset accumulation this should improve incentives for households to build their asset base and climb out of poverty, thereby enhancing economic growth. And as IBLI insures the assets that secure pastoralists' loans, it could crowd in demand and supply for much needed credit, which could further enhance asset accumulation. More importantly, IBLI could protect the vulnerable but presently non poor households from sliding into poverty trap following covariate herd losses, from which they do not recover. Therefore, expected pro-poor role of IBLI is particularly salient in the presence of bifurcations in livestock dynamic leading to a poverty trap in this setting.

The final chapter thus addresses the next critical set of questions: does IBLI affect the wealth dynamics of the target population? If so, will they be willing to purchase it at commercially sustainable rates? And how will these valuations vary across different subpopulations? The success of the product will depend on the existence of adequate demand to make IBLI commercially viable and to establish for national government or development agencies, who might buy IBLI on behalf of poor clients, that it is cost-effective as an instrument for reducing persistent poverty.

The fifth chapter explores these performance issues through simulation analysis. It parameterizes the simulation analysis using household panel data, combined with risk preference estimates elicited in field experiments and historical remote sensing vegetation index data to see how well the IBLI performs in preserving household wealth in a poverty trap economy characterized by bifurcated livestock growth dynamics. This allows exploration of basis risk that has been largely ignored in the empirical literature on IBRTPs in developing countries, as well as resulting inter-household variation in valuation of the IBLI contract. This technique enables us to explore variation of households' willingness to pay and aggregate demand for the IBLI product.

The simulated performance of IBLI contract varies greatly across households and locations with differences in basis risk and in the insured's herd size relative to the bifurcated herd threshold, which determines if and how IBLI alters wealth dynamics. The bifurcation in livestock dynamics leads to nonlinear insurance valuation among pastoralists within the key asset range regardless of their risk preferences. The product performs best among the vulnerable pastoral group, from whom IBLI prevents a catastrophic herd collapse. The estimated aggregate demand for the commercially viable contract is highly price elastic. And because willingness to pay among the most vulnerable pastoralists – those who tend to benefit most from IBLI – is, on average, lower than the commercial premium rates, the chapter concludes by illustrating the potential use of subsidized IBLI to underpin a public safety net properly targeted based on easily observed characteristics such as herd size. This shows promise as a cost effective poverty reduction instrument.[5]

Overall, the IBRTPs developed in this dissertation show considerable promise as effective new risk management instruments to aid populations facing poverty traps of the sort observed in northern Kenya. By addressing serious problems of covariate risk, asymmetric information and high transaction costs that have precluded the emergence of commercial insurance in these areas to date, these products offer a novel opportunity to use financial risk transfer mechanisms to address a key driver of persistent poverty. The potential applicability of the IBRTP ideas developed here extends well beyond the northern Kenyan context. Because extended time series of remotely sensed data are available worldwide at high quality and low cost, wherever there also exist longitudinal household-level data on an insurable interest, similar types of products can also be designed and tested using the methodologies developed in this dissertation.

[5] Barrett et al. (2008) show that an asset safety net akin to this sort of insurance offers superior economic growth and poverty reduction outcomes relative to budget neutral regular cash transfers in the presence of poverty traps.

CHAPTER 2

USING WEATHER INDEX INSURANCE TO IMPROVE DROUGHT RESPONSE FOR FAMINE PREVENTION*

2.1 Introduction

There is a strong link between weather and the welfare of poor populations. Low-frequency, short-term, but catastrophic weather shocks can trigger destructive coping responses to disaster—e.g., withdrawal of children from school, distress sale of assets, refugee migration, crime—and severe human suffering. Moreover, these adverse impacts often persist as children's physical growth falters, and household productivity, asset accumulation and income growth are dampened (Dercon and Krishnan 2000; Hoddinott and Kinsey 2001; Hoddinott 2006). The prospect of such shocks may also induce underinvestment in assets at risk, limiting poor households' ability to grow their way out of poverty over time (Carter and Barrett 2006).

The problem originates with the difficulty poor households face in insuring covariate risk. While informal social insurance arrangements and flexible credit contracts often provide the poor with significant insurance against household-specific, idiosyncratic risk, when entire communities or social networks confront the same biophysical shock, their capacity to buffer members' welfare may be insufficient to prevent severe and widespread human suffering. The magnitude and intensity of such suffering sometimes merits the label "famine" (Howe and Devereux 2004). External (domestic and international) relief organizations and governments commonly step in

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to provide emergency assistance in the wake of catastrophic covariate shocks such as drought, especially when the specter of famine looms. Operational agencies and the donor community are thereby financially exposed to catastrophic weather risks in developing countries via their humanitarian commitment to emergency response.

In addition to their potential for other purposes (Barnett, Barrett and Skees 2006; Alderman and Haque 2007), recent innovations in index insurance show promise as a means to facilitate improved emergency response to weather-related catastrophic shocks that threaten famine. Just as improved early warning systems and emergency needs assessment practices have used timely monitoring and analysis of vulnerable areas to significantly improve humanitarian response in recent decades (Barrett and Maxwell 2005), so too can weather index insurance facilitate further improvement by addressing several key remaining weaknesses in global famine prevention efforts. This paper briefly outlines how donors and operational agencies might use weather index insurance for famine prevention, enumerates key prospective benefits from such products, and then illustrates the possibilities with an application to the arid lands of northern Kenya, an area of recurring severe droughts that elicit massive international humanitarian responses.

2.2 How to Use Weather Index Insurance for Famine Prevention

Weather index insurance pays claims based on realizations of a weather index that is highly correlated with an outcome variable of interest. The insurance policy specifies an event or threshold at which payments are triggered and a payment schedule as either a lump sum or a function of index values beyond that threshold. The pricing of the product is based on the underlying payment schedule and the probability of realizations of the index that might trigger indemnity payments. Those probabilities are typically derived from historical rainfall records (Turvey 2001).

In slightly more formal terms, the key to designing a weather index insurance product is the existence of some observable relationship, $y = f(W, X) + \varepsilon$, where *y* is some outcome variable of interest, *W* represents one or more weather variable of interest (e.g., rainfall), *X* are other covariates that condition changes in *y* and that may be correlated with *W*, $f(\cdot)$ is a general function, and ε is a standard mean zero disturbance term. One will typically use time series observations on the variables to estimate some parametric relation that may involve multiple lags of the independent variables, polynomials in those lags to allow for nonlinearities, etc. The key is that the specified relationship explains much of the variation in *y* and successfully forecasts out-of-sample.

Assuming $f(\cdot)$ is invertible, and given a threshold level of *y* at which one wants to trigger a response, $\bar{y}$, and observable *X*, one can specify and estimate a version of the previous equation and then recover a trigger level for *W*, W^* (Turvey 2001) at which $E[f(W, X)] = \bar{y}$. Thus $f^{-1}(\bar{y}, X) = W^*$. It is also possible to estimate the pure reduced form relation $y = h(W) + \psi$ and similarly derive a threshold value for the weather index $\hat{W}$ if one cannot observe *X* or if the cost of making such observations exceeds the marginal gains in predictive accuracy. The value of the pure reduced form is that the forecasted human impact conditional on observed weather $h(W)$ depends solely on observed weather, and thus it is objective, verifiable and independent from human manipulation. Therefore, $f(W, X)$ and $h(W)$ offer two alternative forms for a parametric index that proxies the risk associated with observed weather events.

Most commonly, the outcome variable reflects economic losses. In the present case, however, we are interested in measures of severe, widespread human suffering, i.e., of famine. The dependent variable we use is the proportion of children aged 6-59 months in a community who suffer a mid-upper arm circumference (MUAC) z-score ≤ -2. As a measure of wasting, MUAC reflects short-term fluctuations in nutritional stress and is typically easier and less costly to collect than weight-for-height, the most commonly used anthropometric measure of wasting. Furthermore, several studies have found MUAC a far better predictor of child mortality than weight-for-height (Alam et al. 1989; Vella et al. 1994). We follow Howe and Devereux's (2004) definition of famine as a condition where 20% or more of children in a specified area are severely wasted (z ≤-2).

Historically, "most famines in poor economies are associated with the impact of extreme weather … [and] the worst famines have been the product of back-to-back shortfalls of the staple crop" (Ó Gráda 2007, p.7). While weather shocks are neither necessary nor sufficient to induce famine, there is a strong historical correlation that can potentially be exploited. Our preliminary work with detailed data from three districts in northern Kenya finds a strong historical relationship between community-level MUAC indicators—in particular, the proportion of a community's children with MUAC z-score≤-2—and lagged rainfall indicators, with considerable out-of-sample forecast accuracy (Mude et al. forthcoming). This offers a promising platform on which to build weather insurance for drought response.

2.3 The Potential Gains of Weather Index Insurance for Drought Response

There have been a number of recent experiments with weather index insurance programs for protection against disasters. The best known example is the Mexican public reinsurance program, Agroasemex, which has marketed weather index insurance policies to state governments to insure against drought, and which has links to the national natural disasters social fund, FONDEN (Alderman and Haque 2007).

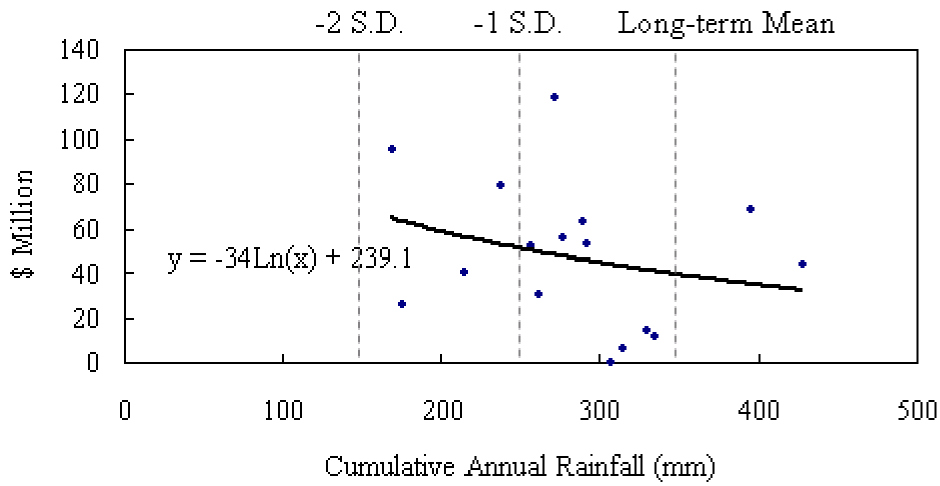
Weather insurance offers several different, potentially major improvements to the global response to climate-related, slow-onset emergencies such as drought. First, insurance by its nature enables the insured to smooth its stream of payments. Rather than incurring irregular, massive expenses for emergency response, one pays a far smaller amount regularly in the form of insurance premia, but receives large indemnity payments when resources are needed. Given liquidity constraints and the value to expenditure smoothing, such smoothing should be advantageous to operational agencies and donors if such insurance can be reasonably priced in the market.

Second, the irregularity of need for famine prevention resources underscores the value of insurance for low-probability, high-impact events as part of an effective risk layering strategy. Communities can easily absorb modest variability in rainfall. In our setting, pastoralists in northern Kenya have developed highly adaptive livelihood strategies over many centuries of coping with volatile rainfall patterns. So a layer of individual and community-level self-insurance is feasible. Bigger covariate shocks commonly demand some outside interventions. Agencies and donors can readily handle small-scale crises within their usual budgets and operational mandates. The problem emerges when rare, widespread and devastating shocks occur and probabilistically threaten famine. With insurance in place to provide resources necessary for such low frequency but potentially catastrophic weather events, other actors can focus better on insuring the range of commonplace risks over which they possess comparative advantage.

Third, index insurance would permit an improved and immediate link between emergency response and recipient need. With most emergency response still based on the provision of food aid that remains tied to procurement, processing and shipment from donor countries, drought response for famine prevention remains doubly tied: to food as the primary form of response and to donor countries as the primary source of that food. Indeed, a common quip in Ethiopia is that the availability of food aid depends not on whether it rains locally, but on whether it rains in North America. Put differently, the supply of food aid—which is a complex function of donor country harvests and farm support policies, global prices, freight costs, geopolitics, etc.—remains as important a determinant of food aid deliveries as is the need of at-risk populations. This is partly reflected in Figure 2.1, which plots rainfall realizations in the three northern Kenya districts we study (Marsabit, Samburu, Turkana) against the value of World Food Programme (WFP) food aid deliveries into Kenya.[6] Over the period 1991-2006, this relationship was quite weak (r^2=0.061 on the best fit, single log specification), and the difference between maximal and minimal annual food aid flows over the period vary by only $31 million even though rainfall volumes in the best year were more than 250% greater than those in the driest year. Current food aid programs are not responsive enough to drought shocks, at least partly due to supply-side obstacles that could be reduced via the proposed weather index insurance, which links cash payouts entirely to predicted humanitarian need.

Fourth, timely and adequate funding are huge obstacles to effective response to slow-onset disasters such as drought. The United Nations' Consolidated Appeal Process (CAP) attempts to coordinate global cooperation in emergency response. On average, however, funds raised via CAP amounted to only 56% of requirements by the end of October in 2003-6 (OCHA). WFP Emergency Operations (EMOP) covers the majority of the humanitarian response, especially related to food security and famine

[6] The food aid figures, obtained from WFP annual reports, reflect deliveries into the whole of Kenya, not just the northern three districts we study. Unfortunately, we could not obtain district-level disaggregated figures. However, these three districts were among the leading recipients of food aid within the country over this period, thus we are confident that the basic patterns are satisfactorily reflected in these data.



Note: Cumulative annual rainfall data are averaged across the three districts. Long-term mean represents the mean cumulative annual rainfall, 1961-2006. S.D. represents the standard deviation.

Figure 2.1 Cumulative Annual Rainfall and Food Aid Expenditures in Kenya, 1991-2006

prevention. While WFP's experience is better than that of the CAP, it too suffers significant shortfalls and delays. On average, only 70% of EMOP funding needs were provided by donors in 2001-2006, ranging from 57% in 2005 to 79% in 2004, and each year, only an average of 36% of EMOP needs were confirmed for donors' contributions by the beginning of June for early intervention with as low as 22% need fulfillment in mid 2004 (WFP). Moreover, donor contributions take months to arrive. For example, the median response time for U.S. emergency food aid is just under five months from the filing of a formal request (a "call forward") to port delivery (Barrett and Maxwell 2005). Delays are costly, even deadly. As an emergency progresses, unit costs per beneficiary increase sharply as more expensive, processed commodities become increasingly needed for therapeutic feeding, donors pay premia for faster transport (including airlift), and populations migrate to camps where broader support costs (e.g., shelter, water, medical care) become essential. Moreover, late arriving assistance often fails to protect the livelihoods of affected populations, who often must deplete their productive asset stocks or migrate in response to the shock, which in turn makes them more vulnerable to future shocks.

In spite of significant improvements in early warning systems, supply chain management and other key response functions, operational agency interventions continue to lag behind global media reporting on disasters. The 2004-5 Niger emergency provides a disturbing example. After a November 2004 international appeal by the Government of Niger and the United Nations, WFP's initial food deliveries in February 2005 cost $7 per beneficiary. But global response was anemic. In June 2005, the Niger situation was relabeled an "emergency," and graphic global media coverage in July-August led to a sizeable, but slow global response. The cost per beneficiary for WFP's August deliveries—i.e., the same delivery organization, but with badly delayed response—had risen to $23, more than three times the cost six months earlier, due to far greater need for supplemental and therapeutic foods instead of cheaper, bulk commodities, and the need for airlift and other quicker, but more expensive logistics. By enabling rapid payout when the trigger is reached rather than merely starting an appeals process likely to drag on for months and be only partly filled, weather insurance can substantially reduce drought response costs and provide greater asset protection to affected peoples.

Finally, because index insurance is based on the realization of a specific-event outcome that cannot be influenced by insurers or policy holders (e.g., the amount and distribution of rainfall over a season), it has a relatively simple and transparent structure. This makes such products easier to understand and consequently to design, develop, and trade, potentially opening up new sources of finance for emergency drought response and famine prevention. The apparent success of pilot programs conducted in India, Malawi, Mexico, Mongolia and various other countries has established the feasibility and affordability of such products (World Bank 2005). Weather insurance contracts underwritten by domestic insurers and reinsured or underwritten directly by international investors can provide a new and cost-effective means to transfer low-probability, high-consequence covariate weather risks to global markets where those risks can be easily pooled and diversified as part of global portfolios. If rainfall volumes provide a strong predictive signal of imminent famine, and thus of looming financing needs for emergency drought response, the opportunity exists to design weather insurance to facilitate more effective aid response. This opportunity should be seized.

2.4 Rainfall and Famine in Kenya: The Potential of Weather Index Insurance

The arid areas of northern Kenya are largely populated by marginalized pastoral and agro-pastoral populations that traditionally rely on extensive livestock production for their livelihood. We focus on three districts—Turkana, Samburu and Marsabit—not only because they are the three districts rated most vulnerable to food insecurity, but also because they share similar socioeconomic characteristics, climate patterns, natural resource endowments, and livelihood portfolios, which allows us to apply similar concepts and tools to drought response across this vast area.

The unpredictability of rainfall heavily affects livelihood returns and welfare dynamics in pastoral communities. To observe such dynamics, Mude et al. (forthcoming) generated community-level summary statistics of repeated cross-sectional household data collected monthly in 45 communities in these three districts from 2000-2005 by the Government of Kenya's Arid Lands Resources Management Project (ALRMP), which resides within the Office of the President, underscoring the importance of drought response in these regions. The key dependent variable is the proportion of children aged 6-59 months in each community with recorded MUAC z-score ≤ -2.

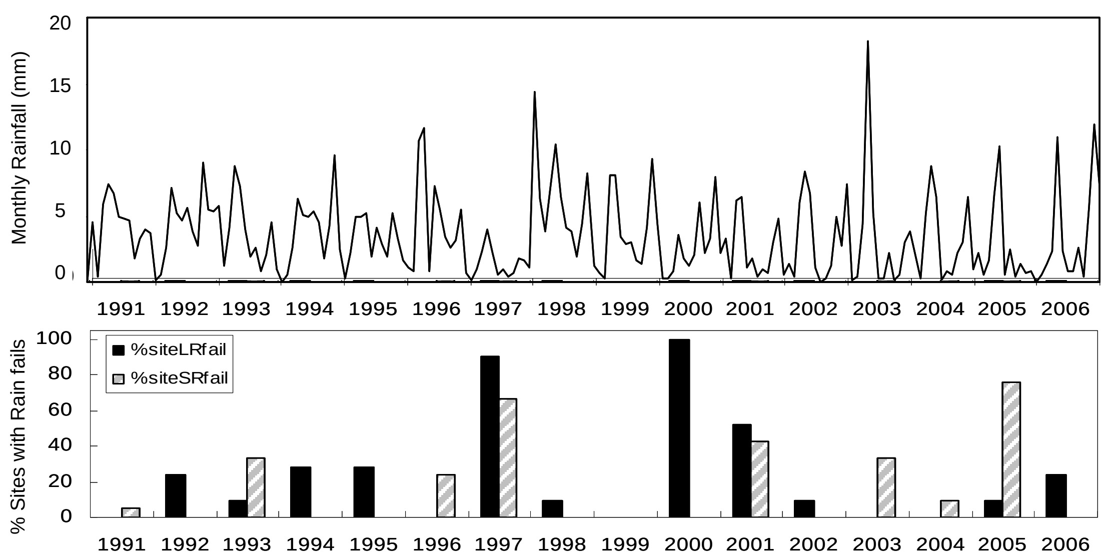
Mude et al. (forthcoming) matched the ALRMP data with forage availability data from the USAID Global Livestock CRSP Livestock Early Warning System (LEWS) and Livestock Information Network and Knowledge System (LINKS) project, and with METEOSAT-based rainfall series, 1961-2006, from 21 geographically distinct sites in these three districts. While floods occur and cause major losses, the primary weather-related risk in these districts is severe drought. Rainfall is generally bimodal, characterized by long rains that fall from March through May and short rains from October through December. Rainfall is also highly correlated across space in these districts. Table 2.1 displays the bivariate correlation coefficients of mean district-level cumulative seasonal rainfall, 1961-2006, with the long rains on the lower diagonal and the short rains on the upper diagonal. The high correlations among these series—all are statistically significantly different from zero at the one percent level—signal limited weather risk pooling potential in northern Kenya, hence the need for outside assistance when severe droughts strike.

Table 2.1 District-Level Seasonal Rainfall Correlations, 1961-2006

District	Turkana	Marsabit	Samburu
Turkana		0.60	0.90
Marsabit	0.71		0.72
Samburu	0.86	0.87	

Pastoralists rely on both rains for water and pasture for their animals, as well as occasional dryland cropping. In a normal year, water availability suffices to ensure adequate yields of milk, meat and blood, most of which is consumed within pastoral households, with the rest sold in order to purchase grains and non-food necessities. Localized rain failures may happen, but migratory herders can commonly adapt to spatiotemporal variability in forage and water availability. But when the rains fail across a wide area, especially if short and long rains both fail in succession, catastrophic herd losses often occur and bring with them severe human deprivation manifest in, among other indicators, more prevalent severe child wasting.

Figure 2.2 plots mean monthly rainfall volumes across these three districts along with the percentage of the 21 sites in which the short and/or long rains failed, where "failure" reflects cumulative rainfall more than one standard deviation below its long-term, site-specific mean. Three major recent droughts had dire humanitarian consequences: 1997/8, 2000/1 and 2005/6. Aggregate rainfall was low in all of these



Note: Monthly rainfall data are averaged across the three districts.

Figure 2.2 Historical Monthly Rainfall and Percent of Sites with Failed Rains, 1991-2006 years, and the drought conditions were spatially widespread and continued across multiple seasons. Mude et al. (forthcoming) show that drought episodes are strongly associated with dramatic herd losses due to mortality, lower livestock lactation rates and a sharply higher prevalence of severe child wasting. Intriguingly, they also find that forecasts of severe wasting prevalence generated from a relatively simple model based on a small set of variables that ALRMP regularly monitors yields highly accurate out-of-sample forecasts with a lead of three months. Rainfall is the key explanatory variable. It seems that observed rainfall patterns may be useful in predicting and insuring against famine.

In this setting, designing weather index insurance to facilitate financing of drought-related humanitarian response appears attractive. We conceptualize two ways in which weather insurance can be effectively designed to serve this goal. The first is a simple put option based on cumulative long rains (March-May) and /or cumulative short rains (October-December)—appropriately weighted across rainfall sites—as a weather index. This might pay out some pre-determined sum per mm shortfall of seasonal cumulative rainfall relative to a contractually established threshold at the end of the contract term for each season. To take into account the intensity of droughts in cases of severe rainfall deficit, the option payout could be a convex function of the seasonal cumulative rain shortfall. Payout could be even simpler, a lump sum payment at the end of the contract term if seasonal cumulative rainfall fell below the threshold. As historical data show that seasonal rain shortfalls are strongly associated with the emergence of famine conditions, even such simple insurance seems to offer a reasonable hedging tool for organizations committed to humanitarian drought response. The simple nature of such contracts can potentially increase reinsurance opportunities and thus lower the prospective price of such insurance in international markets. As local droughts within districts can effectively be handled by traditional means, it might also be more cost effective to write a single contract for the whole area rather than for each district separately.

The second weather index insurance design exploits the apparent ability to forecast famine based on rainfall several months ahead. Specifically, one could use a validated forecasting model to establish the rainfall level below which the expected future prevalence of child wasting equals or exceeds 20%, thereby triggering indemnity payments under the insurance contract. The model would be specified in the contract and new forecasts generated in near-real-time based on the arrival of weather data. The weather index evolves continuously and can therefore better capture not only the impact of shortfalls in rainfall quantity but also the timing and distribution within a season as well. The forecast model can readily incorporate monthly or seasonal dummy variables and location-specific dummies, in short, any other covariates that affect the dependent variable of interest that can be objectively verified and can not be manipulated by parties to the contract. The non-standard nature of this contract might make it somewhat harder to price and sell in financial markets. Weather-based famine index insurance of this sort could complement existing appeals-based systems based more on realizations of human suffering, thereby facilitating faster, lower-cost intervention based more directly on anticipated need and less on supply-side conditions in food aid donor countries.

The famine insurance we envision, especially the second variant, differs in a few key ways from the well-publicized drought insurance contract that WFP took out for Ethiopia with AXA Re in 2006. First, that contract did not use any weather stations from the country's pastoral regions, on which we focus. Second, the weather risks were quantified in terms of expected income loss by at-risk populations based on estimates of the elasticity of crop production to rainfall at different stages of crop growth. Crop- and area-specific estimates were aggregated, mapped to income via price estimates, and then converted into a livelihood loss index. Our design is to tie rainfall directly to a human outcome of interest rather than to indirect measures and to use the commonplace superiority of reduced form forecasting over those based on structural models. Third, the 2006 Ethiopia drought insurance contract covered the entire agricultural season, consisting of two rainy seasons, from March to October, and triggered payment by the end of the contract (in October) when data gathered throughout the contract period indicated that rainfall was significantly below historic averages, pointing to the likelihood of widespread crop failure. The product we envision would pay out at any time within the contract period once the model predicts a prevalence of severe child wasting that meets or exceeds the pre-specified trigger level. Thus, if the seasonal rains failed badly and widely, this might trigger indemnity payments well before the end of the contract so as to allow more effective and lower cost intervention. In parallel work, we explore the theoretical framework for pricing such contracts (Chantarat et al. 2008).

CHAPTER 3

IMPROVING HUMANITARIAN RESPONSE TO SLOW-ONSET DISASTERS USING FAMINE INDEXED WEATHER DERIVATIVES*

3.1 Introduction

Climate variability and extreme weather events are among the main risks affecting the livelihoods and well-being of poor populations. In sub-Saharan Africa, around 140 million people are exposed to the constant threat of famine induced by natural disasters such as droughts and floods. The capacities of communities, social networks or families to buffer members' welfare are, however, insufficient to prevent widespread hunger and severe human suffering when covariate shocks hit. Due to limited insurance against covariate weather risks, short duration but highly catastrophic shocks can have serious long-term consequences for children's growth, household productivity, asset accumulation and income growth (Dercon and Krishnan 2000; Hoddinott and Kinsey 2001; Dercon and Hoddinott 2005; Hoddinott 2006).

Governments, external relief organizations and players in the international aid community commonly step in as insurance providers of last resort for vulnerable populations, providing emergency response to humanitarian crises in the wake of extreme weather shocks. Their commitment to humanitarian relief exposes operational agencies and donors financially to catastrophic weather risks in developing countries worldwide. As the frequency and intensity of natural disasters and food emergencies

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have increased in recent decades (Munich Re 2006), so has the number of people needing humanitarian assistance, requiring more resources from external agencies and donors. With limited available funds to support emergencies, rigorous tools for efficient planning and prioritization of interventions and resource allocation become crucial to enhance the humanitarian and economic value of emergency operations.

Recent innovations in weather derivatives[7] and the booming market for transferring covariate weather risks provide considerable promise to mitigate weather-related catastrophic shocks that threaten humanitarian crises. Improved early warning systems and emergency needs assessment practices have used timely monitoring and analysis of situations in vulnerable areas to significantly improve humanitarian response in recent decades (Barrett and Maxwell 2005).

The goal of this paper is to show how weather derivatives can be designed and used by governments and operational agencies to improve humanitarian response to slow-onset disasters, especially drought. The contracts we propose, "famine indexed weather derivatives (FIWDs)", comprise two main characteristics. First, the weather variables used to trigger contract payouts need to be indexed to some indicators of forecasted prevalence and severity of food insecurity conditions in the targeted areas, and second, the timing and frequency of the cash payouts need to facilitate potential early interventions.

We motivate this idea by briefly reviewing current innovations in the weather derivatives market and its potential in developing countries. The rationale for FIWDs and the contracts' main characteristics are then described. We then provide a general framework for two distinct contract structures – weather index insurance and a famine catastrophe bond – and explain how developing country governments and

[7] We refer to weather derivatives loosely as financial contracts that derive values from weather variables. In this context, weather derivatives may thus refer to weather index insurance offered by reinsurers, weather indices or weather related contracts traded in the exchange.

international organizations might combine these derivative products with other funding opportunities – e.g., contingent grant or debt from international development banks – to enhance catastrophic risk transfer opportunities and to obtain cost-effective catastrophic risk financing (Hess et al. 2006; Syroka and Wilcox 2006; Hess and Syroka 2005). Finally, we illustrate the possibilities with an application to the arid lands of northern Kenya, an area that suffers recurring, severe droughts that often require a massive international humanitarian response to avert famine.

3.2 Weather Derivatives and Their Potential in Developing Countries

A weather derivative is a type of parametric contingent claim contract whose payoff schedule depends on a measure of meteorological outcomes – such as inches of rainfall – at a certain location during the contract period (CME 2002). The weather derivative contract specifies a specific event or threshold that triggers payments and a payment schedule as either a lump sum payment or a function of index values beyond that threshold. A variety of derivatives can be issued on well-specified weather variables or a single- or multiple-specific weather event (Turvey 2001; Dischel 2002). The most common types of contracts are put and call options – mostly seen in the form of weather indexed insurance, – swaps and collars.

If weather variables are highly correlated with covariate economic loss, derivatives on appropriate weather variables can be used to effectively hedge against such loss. The contracts can be written on various weather risks, and traded like financial assets. The weather derivatives market thus provides opportunities for covariate weather risks to be transferred and managed either as part of a diversified global weather risk portfolio – weather risks in Kenya, for example, are potentially uncorrelated with those in other geographic areas – or as part of a diversified capital market portfolio (Froot 1999; Hommel and Ritter 2005). The weather derivatives market has grown dramatically, to the notional value of USD 19.2 billion in 2006/7, from USD 2.5 billion in 2001/2.[8] To date, the market has expanded to cover weather risks outside U.S., Europe and Japan.

Among the popular products, catastrophe (cat) bonds are weather derivatives that have primarily been issued by reinsurance companies to facilitate transfer of the risk of highly catastrophic events with very low annual loss probabilities (mostly less than 1 percent per annum) to capital markets. Cat bonds are typically high-yield derivatives with the return conditional on well-defined weather conditions indicating the occurrence of a catastrophic event.

From the perspective of the investor, cat bonds yield above-market rates (typically 3-5% spread over LIBOR (Bantwal and Kunreuther 2000; Banks 2004) encompassing various compensating premiums[9], while offering diversification. There is thus an increasing appetite for these products in the market. Hedge funds, institutional money managers, commercial banks, pension funds and insurance companies are regularly investing in cat bonds. The market to date is concentrated in reinsurance of U.S. hurricane and Japanese earthquake risk, but has been extended beyond natural perils providing risk coverage against epidemics and man-made disasters.

The total market size grew to almost US$ 5 billion in 2005 (Guy Carpenter 2006), and it is expected to continue trending upward as the cost of issuing declines with the development of more standardized bond structures and as the investor base

[8] The survey has been conducted yearly by the Weather Risk Management Association (WRMA) and PricewaterhouseCoopers. For further detail see http://www.wrma.org.

[9] Apart from the risk premium on comparably rated corporate bonds, premiums are needed to compensate for ambiguity about probability of the rare catastrophic events, costs of the learning curve for a complex product and market, and loss aversion which results in overvaluation of loss probability (Bantwal and Kunreuther 2000; Banks 2004; Nell and Richter 2004).

expands and becomes more knowledgeable (Bowers 2004). Recently, there has been an attempt to design cat bonds to securitize systemic risks in agriculture (Vedenov, Epperson and Barnett 2006). Cat bonds – or at least the principles that underpin then - might serve as a means to transfer highly catastrophic but low probability weather risks from developing countries to the global capital market (Hofman and Brukoff 2006).

The weather risk market also facilitates reinsurance opportunities. For example, Indian weather risks are currently reinsured in the weather derivatives market, allowing local insurance companies to sell weather insurance against drought to small farmers since 2002. The Mexican public reinsurance company Agroasemex has similarly provided weather index insurance to state governments to protect farmers against drought in most of the dry-land areas since 2001. Weather insurance contracts are also currently sold in Malawi, Tanzania and Thailand as part of pilot programs.[10]

The market also facilitates transfer of highly catastrophic weather risks that can trigger emergency needs by governments, donors or international humanitarian organizations (Hess et al. 2005; Alderman and Haque 2007). The United Nations World Food Programme (WFP) successfully took out US$ 930,000 in drought insurance from an international reinsurer, AXA Re, for Ethiopia's 2006 agricultural season covering 17 million people at risk of livelihood loss (WFP 2005). In December 2007 the World Food Programme (WFP) announced that it was expanding "the first humanitarian insurance policy" in Ethiopia, hoping to raise US$230 million in insurance and contingency funds to cover 6.7 million people if there is a drought comparable to the one in 2002/2003 (IRIN Africa 2007). In addition, the Mexican government issued a US$160 million cat bond to insure their National Fund for

[10] Various weather index insurance products are currently being developed in Bangladesh, Honduras, Kazakhstan, Morocco, Nicaragua, Peru, Senegal, Vietnam and several of the Caribbean islands (Barnett and Mahul 2007).

Natural Disasters (FONDEN) against the risk of a major earthquake in 2006 (Hofman and Brukoff 2006; Guy Carpenter 2006). Similar products currently being explored include a Caribbean Catastrophe Risk Insurance Facility aimed at allowing Caribbean countries to pool and transfer natural disaster risks to the capital market (World Bank 2006), and multinational insurance pools for the Southern African Development Community (SADC) that can facilitate transferring catastrophic weather risk as part of a regional strategy to obtain reinsurance cost reduction (Hess and Syroka 2005). The World Bank is also currently establishing a new reinsurance vehicle, the Global Index Insurance Facility (GIIF), as a risk-taking entity to originate, intermediate and underwrite indexable weather, disaster and commodity price risks in developing countries (World Bank 2006).

3.3 Using Weather Derivatives to Improve Emergency Response to Drought

3.3.1 Rationale

While weather shocks are neither necessary nor sufficient to induce widespread humanitarian crises, there is a strong historical correlation (Dilley et al. 2005; Ó Gráda 2007) that can potentially be exploited. The effectiveness of humanitarian response to weather-induced crises depends not only on the quantity of aid provided but when and how assistance is provided. Timely delivery of food, medicine and other essential supplies is crucial to effective emergency response.

Since slow-onset disasters such as droughts exhibit predictable patterns, drought-induced humanitarian crises may be somewhat predictable. When seasonal rains fail to arrive, agricultural production generally deteriorates, leading to increasing food shortages and prices, depressed rural livelihoods and acute food insecurity. Progress has been made by local governments and operational agencies – e.g., United

Nations agencies such as WFP and FAO – in developing credible emergency need assessments and reasonably accurate early warning systems[11] that can identify where and when to intervene, and at what scale. However, resources are limited in part by a general lack of timely and reliable funding to respond to emergency needs. At present, the main mechanism for financing emergency operations is through the appeal process, where early warning systems trigger a field emergency needs assessment that leads to an international appeal for appropriate funding. The main problem with this approach is that donor funding is unreliable and often quite delayed with actual humanitarian delivery taking as long as four to eight months (Morris 2005; Haile 2005). Delays are costly. As an emergency progresses, unit costs per beneficiary increase sharply as more expensive, processed commodities become increasingly needed for therapeutic feeding, donors pay premia for faster transport (including airlift), and populations migrate to camps where broader support costs (e.g., shelter, water, medical care) become essential, etc. In the 2004-5 Niger emergency, for example, the cost for WFP's deliveries had increased from $7 to $23 per beneficiary due to six-month delayed response.

3.3.2 Famine-Indexed Weather Derivatives

The most crucial attribute of weather derivatives for any humanitarian response system is the capacity to make immediate cash payouts for timely emergency intervention. The key to designing weather derivatives to improve emergency response to slow-onset disasters such as droughts is a well-established correlation between the specific event weather variable (s) and estimated humanitarian needs, and an

[11] Programs such as the Global Information and Early Warning System (GIEWS), WFP's Vulnerability Analysis and Mapping (VAM), the Strengthening Emergency Needs Assessment Capacity (SENAC) project and USAID's Famine Early Warning Systems Network (FEWS-NET) currently collaborate and facilitate early warning, and emergency need assessment capacity.

appropriate contractual payout structure. Humanitarian crises often result from successive drought episodes, late arrival of the main rains, or discontinuous rainfall patterns within the season, occurring in spatially widespread locations. Therefore, though simple rainfall volume matters so does the temporal and spatial distribution of rainfall within seasons. Therefore, an appropriate weather derivative contract to properly hedge against widespread suffering should take into account these rainfall variables and events. Such patterns can be clearly observed in the case of arid pastoral areas of northern Kenya, discussed in more detail in our illustration in section 5. Mude et al. (forthcoming) show that drought episodes are strongly associated with sharply higher prevalence of severe child wasting.[12]

Formally, weather variables and other weather-related covariates (*W*) – rainfall volume, distribution, multiple rainfall events, etc. – may be indexed to some indicator of severe and widespread human suffering from food crises (*F*) by an established empirical forecasting model

$$F = f(W) + \varepsilon \tag{3.1}$$

where $f(\cdot)$ is a general function and ε is a standard mean zero disturbance term. The value of this pure reduced form estimation is that the forecasted human impact conditional on observed weather depends solely on observed weather and immutable or exogenous covariates (e.g., location or seasonal dummy variables). It is objective, verifiable and extremely difficult to manipulate. Therefore, $f(W)$ can serve as a parametric "famine index" that forecasts the risk of widespread, severe undernutrition associated with observed weather events. New forecasts may be generated in near-

[12] Among the covariates used in Mude et al. (2006)'s forecasting model are various autoregressive lags of prevalence of severe child wasting, herd dynamics, food aid and forage availability, some of which are not objectively measured. Thus, they may be prone to moral hazard if directly used as triggers for derivative contracts. To develop it further as triggers for weather derivative contracts, slight modifications are needed to ensure that the covariates used are transparent and free from tampering.

real-time based on the arrival of new weather data, so the famine index can evolve over time throughout the contract coverage. This may therefore better capture not only the impact of shortfalls in rainfall quantity in a specific time or season but also the timing and distribution of rainfall within a season or across seasons. Finally, assuming $f(\cdot)$ is invertible, one can recover an extreme weather trigger W^* corresponding to an appropriate critical threshold of forecasted degree of human suffering, F^*, that triggers emergency response intervention such that $W^* = f^{-1}(F^*)$ (Turvey 2001).

3.3.3 Establishing Appropriate Contractual Payout Structures

Since timely financing for effective early intervention is a goal, weather derivative contracts based on the forecast based famine index, $f(W)$, should trigger indemnity payouts as soon as the famine index meets or exceeds the pre-specified thresholds, or allow multiple triggered payouts within the contract term, rather than paying out only at the end of the contract term. Response delays can be costly and even deadly. Thus, if the seasonal rains failed badly and widely the contract might trigger indemnity payments well before the end of the contract so as to allow more effective and lower cost intervention. In the following section, we provide a general framework for such contracts that can be designed and used to improve emergency response to drought.

3.4 Structure and General Framework

Generally, contingent debt or grant facilities offered by the World Bank and other international financial institutions on concessionary terms to developing countries affected by either natural or manmade disasters may be used to support countries' early intervention in response to drought. The catastrophic layer of drought risk, where such facilities are no longer available or suitable to accommodate the emergency need, can then be managed through global financial market mechanisms. For this purpose weather index insurance or catastrophe bonds may facilitate transfer of extreme drought-induced famine risk to market players willing to accept the risk at some cost. We now consider these two forms of famine indexed weather derivatives, which can complement other available financing facilities to hedge against various layers of drought-induced famine risk.

3.4.1 Weather Index Insurance

Weather index insurance can allow governments and/or international aid agencies to transfer drought-induced famine risk to international insurers or reinsurers, most likely with the donor community funding the insurance premium ex-ante. A well-designed contract can be beneficial to both beneficiary and donors alike. On the one hand, if the insurance is triggered, the indemnity payout will be released to a government and/or nongovernmental operational agencies to finance effective emergency response. On the other hand, pre-financing humanitarian aid allows donors to hedge against the risk of volatile demand for overseas development assistance (Skees 2002; Syroka and Wilcox 2006).

We refer to $\Pi_T(W, W^*)$ as the total payoff at the terminal period T of famine indexed insurance contract[13] covering a vulnerable period $[0, T]$ and based on the observed specific weather event (W), the famine index function, $f(W)$, and a pre-specified anthropometric trigger F^*. It is F^* that determines the index trigger $W^* = f^{-1}(F^*)$. Depending on the nature of drought risk and financial exposure of organizations in the affected countries, various index and payout structures can be considered.

[13] Alternatively the insurance payoff can also be structured in terms of direct famine index *f(W)* relative to the anthropometric famine trigger F^*. And thus the payoff $g_T^{'}(f(W), F^*) = Max[C(f(W) - F^*), 0]$.

Famine indexed insurance can be in the form of a simple put option, establishing payout at the end of the contract *T*. Thus,

$$\Pi_T\left(W, W^*\right) = Max\left(C(W^* - W_T), 0\right) \tag{3.2}$$

where $C(\cdot)$ is some function that maps the severity of weather shortfalls relative to the extreme weather threshold to the associated funds required for immediate humanitarian assistance. For example $C(\cdot)$ might be defined by $(W^* - W_T)^x$, where $x \geq 1$, captures the intensity of the famine index relative to the weather event especially if the extent of potential suffering is non-linearly related to precipitation shortfalls. The required funds can be estimated from past emergency operations or can be based on the drought contingency planning system a developing country might already have in place.

To ensure timely funding, weather-linked famine insurance can also be designed to make a payout at any first time *t* within the vulnerable period coverage, $[0, T]$, if the weather index W reaches the threshold W^*. The payoff at terminal period *T* can be written as

$$\Pi_T\left(W, W^*\right) = e^{r(T-t)} C(W^* - W_t) \cdot 1_{t\left(W, W^*\right) \leq T} \tag{3.3}$$

where r is a required rate of return, which, for simplicity, is assumed to be deterministic[14]; 1_A is an indicator function of an event A; $t(W, W^*)$ is the first passage time of W to reach the threshold W^*, and $1_{t(W, W^*) \leq T}$ = 1 is an indicator function designed to capture a trigger at any period *t* within $[0, T]$ and 0 otherwise. The insurance coverage $[0, T]$ can be chosen so that it covers the entire period each

[14] A stochastic required rate of return may be applied as it captures interest rate risk under a variety of assumptions (Heath et al. 1992) and other related risks due to factors other than a catastrophic event. The adjusted discount rate with stochastic required rate of return can be represented by $r(t) = \int_0^t r(s)ds$.

year when people are vulnerable to extreme weather – e.g., the whole rainfall season. Finally, the function $C(\cdot)$ in this digital, down-and-in option may simply represent a lump sum of required funding released to finance baseline early intervention to the forecasted drought event triggered.

Famine indexed insurance can also be designed to cover multiple drought events (usually multiple years (*N*) with one event in a vulnerable period $[0,T]$ each year) and thus to establish multiple triggered payouts at any year *n* within the *N* years coverage. The total payoff realized at the end of the contract at year *N* can be represented by

$$\Pi_N\left(W,W^*\right)=\sum_{n=1}^{N}e^{r(N-n)}\Pi_n(W,W_n^*) \tag{3.4}$$

where $\Pi_n(W,W_n^*)$ represents insurance payoff at terminal date of any year *n* within the *N* years coverage.[15] For example, $\Pi_n(W,W_n^*)=Max[C(W_n^*-W_n),0]$ if a yearly contract is a simple put option. Moreover, a cap of $\overline{\Pi}_n$ can be applied to limit the insurer's maximum loss each year, thereby potentially increasing market supply. The total payoff at the end of this contract is

$$\Pi_N\left(W,W^*\right)=\sum_{n=1}^{N}e^{r(N-n)}Min\left(\Pi_n(W,W_n^*),\overline{\Pi}_n\right) \tag{3.5}$$

Furthermore, W_n^* and $\overline{\Pi}_n$ are subscripted, indicating that the trigger and the cap can change over time. If the trigger and the cap are the same in all periods then (3.4) and (3.5) can be converted to simple annuities.

[15] Since the coverage period of *[0,T]* is fixed across years, for simplicity, the yearly contract can be designed such that the terminal coverage period *T* is also the terminal period of a year. Hence, the period between the end of year 1 and the start of the contract, $T_1-T_0=1$ year and the period between the end of contract and the end of any year *n*, $T_N-T_n=N-n$ years. Therefore, subscript *T* is dropped from the yearly terminal payoff $\Pi_n(W,W_n^*)$ of any year *n*.

The actuarially fair premium for the insurance contract is calculated by taking the expectation of the insurance payoff with respect to the underlying distribution or process of weather variable, *W*, and discounting the term with appropriate discount rate.[16] Hence, the actuarially fair premium for a famine indexed insurance covering *N* years of drought events (with one event in a vulnerable period $[0,T]$ each year) can be written as

$$Premium = e^{-rN} E^{\omega}\left(\Pi_N (W, W^*)\right) \tag{3.6}$$

where E^{ω} indicates expectation at the beginning of the contract with respect to a state variable ω that pertains to some catastrophic weather risk governed by the underlying distribution of weather variable, *W*. To this fair rate, a loading factor $m > 1$ is usually added to capture the insurer's attitude toward ambiguity of the underlying weather, their opinion about weather forecast and their aversion toward catastrophic risks.

3.4.2 Catastrophe Bonds: Famine Bonds

While weather index insurance contracts can facilitate the transfer of drought risks to international insurers or reinsurers, the extreme layer of the catastrophic weather risks may not feasibly and/or cost effectively be absorbed by a single or a small number of insurers or reinsurers. Extreme drought risks that cannot be absorbed through the reinsurance market using weather index insurance can potentially be securitized and transferred to the capital market in the form of catastrophe (cat) bonds – or simply "famine bonds" in this setting.

Catastrophe bonds are typically engineered as follows. The hedger (e.g., governments, agencies) pays a premium in exchange for a pre-specified coverage if an

[16] If a stochastic discount rate is considered, the premium will have to be calculated based on the joint distribution of weather variable *W* and the appropriate term structure of interest rate.

extreme weather event occurs; investors purchase cat bonds for cash. The premium plus cash proceeds are directed to a special purpose company, generally an investment bank, which then invests in risk-free assets (e.g., treasury bonds) and issues cat bonds to investors. Investors then hold cat bonds whose cash flows – principal and/or coupon – are contingent on the risk occurrence. If the covered event takes place during the coverage period, the special purpose company compensates the hedger and there is full or partial forgiveness of the repayment of principal and/or interest to investors. Otherwise, the investors receive their principal plus interest, which incorporates the associated risk premium.

Conceptually, governments or international organizations can initiate the issuance of zero coupon or coupon catastrophe bonds, for which principal and/or interest payments to bondholders are conditional on the occurrence of extreme drought induced famine identified by the constructed famine index relative to a specified threshold. For government or humanitarian agencies, famine bonds simply offer an insurance function just like weather index insurance for the highly catastrophic layer of drought risk by releasing immediate cash payment for emergency operations once the famine index is triggered. Thus, government and operational agencies finance famine bonds similarly to paying index insurance premiums. They can appeal to the donor community for premium contributions in advance – i.e., in the form of the disaster pre-financing (Goes and Skees 2003).

Generally, the price of a famine cat bond issued at time *0* with the face value P, annual coupon payments c and time to maturity of N years, at which bondholder agrees to forfeit a fraction of the principal payment P by the total insurance payoff $\Pi_n(W, W_n^*)$ at maturity, can be written as

$$B(0,N) = e^{-rN} E^{\omega}\left[P - Min\left[\sum_{n=1}^{N} e^{N-n}\Pi_n(W, W_n^*), \overline{\Pi}\right]\right] + \frac{c}{r}(1 - e^{-rN}) \tag{3.7}$$

where $\overline{\Pi} < P$. A famine bond can therefore be structured as a coupon bond that is embedded with a short position on a weather-linked option based on a trigger established by the famine index – specifically famine indexed insurance. Equation (3.7) is a multi-year bond issue that deducts from principal the indemnity in each year compounded to year N at the continuous compounding rate r and subject to a cap $\overline{\Pi}$ that cannot exceed principal. Like typical bonds, famine bonds are valued by taking the discounted expectation of the coupon and principal payments under the underlying distribution of the weather index and the required rate of return on investment.[17] Alternatively if the coupon $c = 0$ the bond will be issued as a discount bond, and if $N = 1$, a 1-year bond.

The main advantage of securitizing and managing famine risk using cat bonds over index insurance is the potential to avoid default or credit risk with respect to catastrophe reinsurance. The threat of widespread catastrophic losses imposes a significant insolvency risk for reinsurance companies and thus for their capacity to compensate such losses. In contrast, cat bonds permit division and distribution of highly catastrophic risk among many investors in the capital market and so may allow greater diffusion of the extreme weather risk. Moreover, funds invested in a cat bond are collected ex ante, which implies that such credit/default risk is minimized to the default risk connected with the investments made by the special purpose vehicle.

[17] A stochastic rate $r(t) = \int_0^t r(s)ds$ may be used as the adjusted required return representing interest rate risk under a variety of assumptions (Heath et al. 1992) and other related risks due to factors other than a catastrophic event, which can be incorporated into the bond pricing by setting the discount rate $r(t)$ equal to the rate of return required by investors in general bonds of comparable risk.

Comparing the premium costs between the two requires further investigation of market capacity and opportunity.

Empirical pricing of the weather index insurance and famine bonds based on the framework provided above can be done in various ways, depending largely on assumptions, model specifications and the methodology used to derive or calibrate the empirical distribution of the famine index, $f(W)$, and the term structure of interest rates. A variety of such models applied to credit instruments are presented in Turvey and Chantarat (2006) and Turvey (2008). It is arguable that various option valuation models (e.g., the Black-Scholes 1973) widely used in finance are inappropriate in this context. The extreme weather events characterized in the constructed index tend not to follow geometric Brownian motion – thus violating the underlying assumption of the models – as weather patterns tend to be autocorrelated, mean-reverting and exhibit seasonal trends (Dischel 1998; Martin et al. 2001; Richards et al. 2004; see Turvey 2005 for an exception). Moreover, because a weather index does not have a traded underlying asset; unlike a financial index, there is no spot market or price for weather events; applying the principle of risk-neutral valuation or a replicating portfolio to the value of weather options is thus inappropriate (Davis 2001; Martin et al 2001; Hull 2002).

Weather derivatives are frequently priced using actuarial methods (Turvey 2001, 2005). This approach to empirical pricing of index insurance and cat bonds may involve two general steps: (i) estimating the distribution of the weather index and thus the probabilities of triggering the payout, and (ii) incorporating the estimated probability distribution and the required rate of return into the actuarially fair pricing framework provided above. We illustrate these concepts by pricing the illustrative famine indexed weather derivatives for northern Kenya using comparable historical burn rate – which assumes that variability of past weather reflects the expected variability of future weather and therefore uses the observed historical distribution of the weather variable in calculating actuarially fair prices – and Monte Carlo simulation – which simulates the probability distribution of the weather variable using a sufficiently long time series of available weather data and an assumed structure of randomness as the main inputs. Further explorations are needed to allow for price discovery of these innovative weather derivatives in the market.

3.4.3 Incorporating FIWDs to Enhance Effective Drought Risk Financing

The famine index could be used to layer drought-induced famine risks such that financial tools and facilities appropriate for each layer can be applied cooperatively. One possible example – considered also in Hess et al. (2006) and Hess and Syroka (2005) – combines international development banks' debt/grant facilities, index based risk transfer products and the traditional donor appeals process in drought emergency response financing.

Beyond the nation's self-retention layer – i.e., interventions in response to frequent, local and low-loss drought events can be managed using national resources – a famine index could be used as a trigger for the release of contingent grants and/or debt with fixed and pre-established terms to governments or operational agencies for early intervention in emergency response.[18] Combinations of weather index insurance and catastrophe bonds can then be used to transfer the catastrophic layer of drought risks beyond the capacities of the institutional grants/debt facilities.

All in all, a risk manager's decision on an effective risk layering strategy as well as optimal risk allocation arrangements among available strategies and instruments within each layer of risk becomes a problem of minimizing risk financing

[18] The debt triggered may further be attached with the index insurance (Turvey and Chantarat 2006) so that the debt repayment is contingent upon the occurrence of disaster (i.e., when $W^* > W$).

costs – financially and economically – with respect to resource availability and market prices for FIWDs. But timely and predictable payouts from FIWDs now replace delayed and unreliable humanitarian aid in response to severe drought events when FIWDs are used to complement traditional donor appeal processes.

3.5 Potential for Famine Indexed Weather Derivatives in Northern Kenya

The arid areas of northern Kenya are largely populated by marginalized pastoral and agro-pastoral populations that traditionally rely on extensive livestock production for their livelihood, thus particularly vulnerable to covariate shocks in the form of drought and flood. To address the vulnerability of its populations and to improve their ability to manage risks, the Government of Kenya's Arid Lands Resources Management Project (ALRMP) has been funded by the World Bank since 1996 aiming to develop and implement a community based drought management system. A community-based early warning system based on monthly household and environmental surveys that collect detailed information on livelihoods, livestock production, prices and the nutritional status of children is currently used to signal various stages of drought and food insecurity situation and thus to help government and operational agencies manage droughts.

In the context of FIWD design, these survey-based variables may not all be suitable as a direct index to hedge against famine risk as they may be manipulable by prospective beneficiaries. However, since drought episodes are strongly associated with sharply higher food insecurity in the pastoral communities (WFP 2001-2006), the predictive relationship between rainfall variables associated with extreme rainfall events and available food insecurity indicators such as nutritional status of children, levels of exogenous food availability (e.g., existing food aid pipeline commitments), real prices of key staple crops, etc., could be used in a parametric famine index for various derivative contracts.

For illustrative purposes, the relationship between rainfall variability and the directly observed proxy of prevalence and severity of child undernutrition is used to develop a famine index for FIWDs for the study areas.[19] Specifically, we obtained sample readings of the mid-upper arm circumference (MUAC) for children aged 6-59 months in each of 44 communities in 3 arid districts – Turkana, Samburu and Marsabit – for which a sufficient continuous monthly observations from 2000-2005 were available.[20] These three districts are rated most vulnerable to food insecurity and thus their populations are among the majority of Kenyan populations to receive yearly food assistance, making these areas very suitable as an illustrated case for our study.[21]

As a measure of wasting, MUAC reflects short-term fluctuations in nutritional stress and is typically easier and less costly to collect than weight-for-height, the most commonly used and most documented anthropometric measure of wasting. Furthermore, several studies have found MUAC to be a far better predictor of child mortality than weight for height (Alam et al. 1989; Vella et al. 1994). We calculate the proportion of children in each community with a MUAC z-score of -2 or lower[22] and use it as a proxy for widespread acute food insecurity. This coincides with other measures used among operational agencies and in anthropometric research in various

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[19] Other factors such as domestic and international policies or other economic factors may influence pricing variables and so their capacities to truly reflect the needs of the affected population.

[20] Theoretically thirty households are randomly selected per community and they are revisited each month. But the incompleteness due to poor data organization and storage of this repeated cross-sectional household data described in detail in Mude et al. (Forthcoming), a subset of data, for which a sufficient number of continuous observations were available, are suitably chosen for the analysis of community-level impact of covariate shocks.

[21] These three pastoral districts also share similar socioeconomic characteristics, climate patterns, natural resource endowments, and livelihood portfolios according to the WFP's Vulnerability Analysis and Mapping (VAM) pilot study on chronic vulnerability to food insecurity (2001), allowing the application of similar concepts and tools to drought response across this vast area.

[22] MUAC data are standardized using international recognized the 1978 CDC/WHO growth chart. The threshold $z \leq -2$ is consistent with the benchmark often employed by emergency relief agencies to define famine (World Food Programme 2000; Howe and Devereux 2004).

disciplines, for example Howe and Devereux's (2004)'s definition of "famine" as a condition where 20% or more of children in a specified area are severely wasted (i.e., with z-score of an anthropometric measure of malnutrition $\leq$-2) and "severe famine" when 40% or more of children in a specified area are severely wasted. This MUAC measure of the prevalence of severe child wasting can be used to quantify the level of drought-induced famine risks and thus to establish appropriate thresholds that trigger weather derivative payout for emergency response.

We then match these data with the 1961-2006 rainfall series, comprised of 1961-1996 CHARM historical rainfall data estimated from the historical satellite imagery (Funk et al. 2003) and 1996-2006 METEOSAT-based daily rainfall estimates.

3.5.1 Rainfall Variability and Food Insecurity in Northern Kenya

These pastoral areas are generally characterized by bimodal rainfall with short rains falling October-December, followed by a short dry period (January-February) and long rains in March-May followed by a long dry season from June-September. This pattern is shown in Figure 3.1, which plots kernel density estimation of yearly rainfall patterns in the three northern Kenyan districts we study. Pastoralists rely on both rains for water and pasture for their animals, as well as occasional dryland cropping. Dry seasons are typically hunger periods in these pastoral communities.

In a normal year, water availability suffices to ensure adequate yields of milk, meat and blood, most of which is consumed within pastoral households, with the rest sold in order to purchase grains and non-food necessities. Localized rain failures may happen, but migratory herders can commonly adapt to spatiotemporal variability in forage and water availability. But when the rains fail across a wide area, especially if short and long rains both fail in succession, catastrophic herd losses often occur and

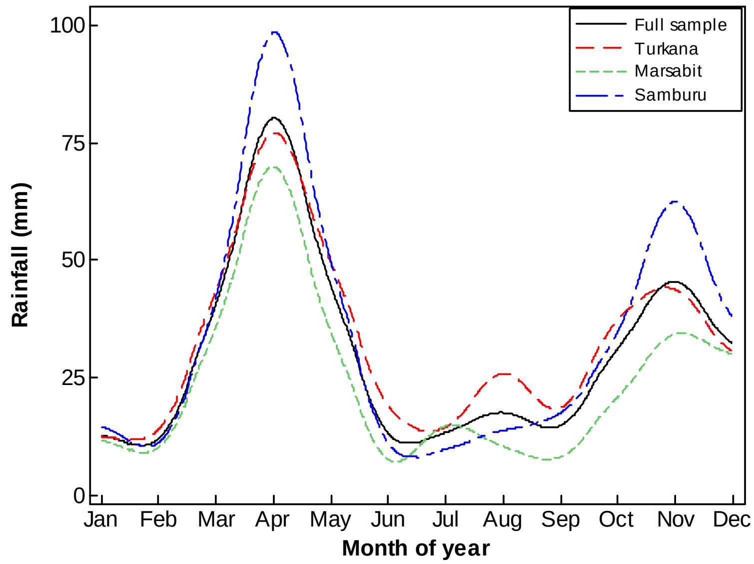

Figure 3.1 Kernel Density Estimation of Yearly Rainfall Pattern in Three Pastoral Districts of Northern Kenya, 1961-2006

major recent droughts with dire humanitarian consequences – 1997/8, 2000/1 and 2005/6 – were all years in which not only was aggregate rainfall low, but it was also spatially widespread and continued across multiple seasons. Moreover, evidence of the effect of variability in seasonal rainfall on the prevalence and severity of malnourished children can be clearly observed in the following dry season, as in Figure 3.2, which plots the dynamics of rainfall and nutritional status characterized by the proportion of severely wasted children in a community from 2000-2005 in these three districts we study the impact of 2000's failed long rains resulted in a larger proportion of malnourished children in the following long dry season, whereas the localized failure of the 2003 short rains resulted in a temporary peak in proportion of malnourished children in the following short dry season at the start of 2004.

Kenya's current drought response system is illustrated in Figure 3.3. Seasonal rain forecasts are conducted two months before the start of the seasonal rains with the

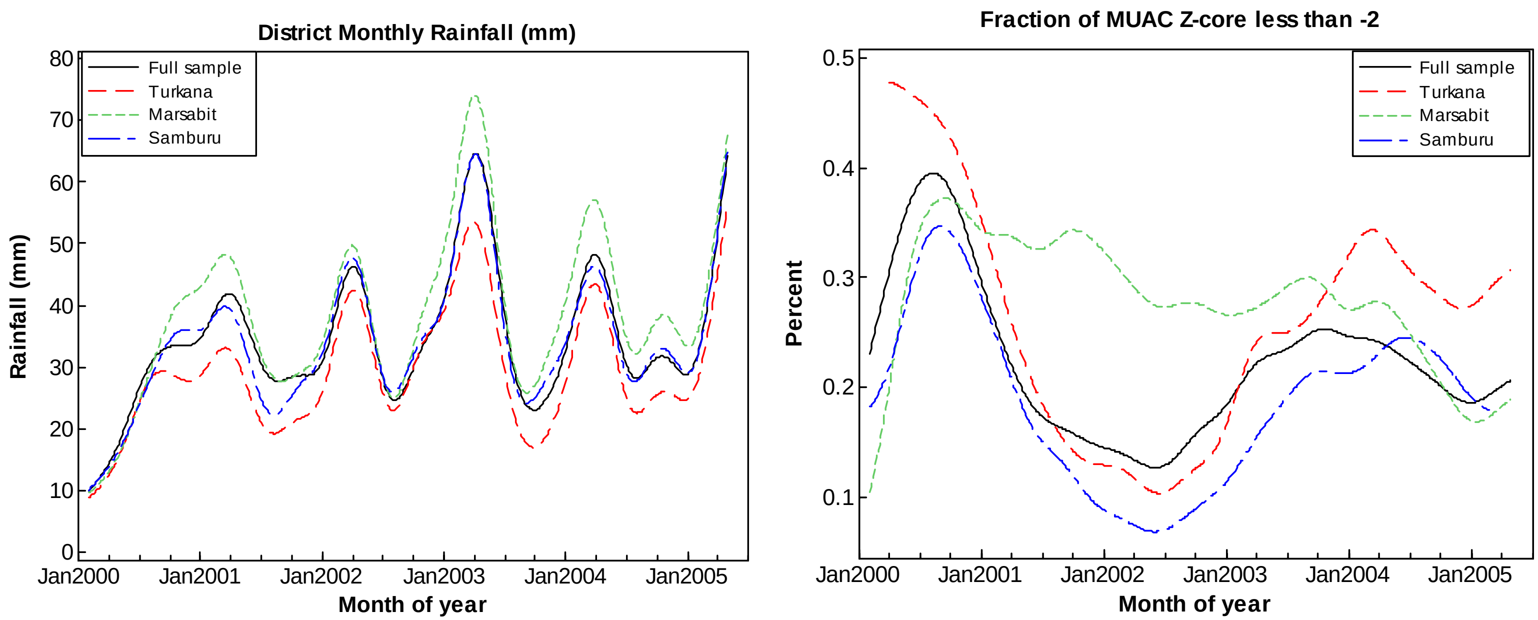

Figure 3.2 Kernel Density Estimations of Monthly Rainfall and Proportion of Severely Wasted Children, 2000-2005

goal to produce early warning to help herders improve their livelihood decisions as well as to facilitate drought response planning among agencies. Approximately two-month-long seasonal rain assessments then take place after the end of the seasonal rains. These result in estimates of the affected populations and the associated funding needs, information which is then used in the donor funding appeals. It usually takes at least 5 months from the end of each rainy season until the newly programmed humanitarian aid is actually delivered. Consequently aid delivery under the current response system might fail to preserve livelihoods or even the lives of some affected populations.

3.5.2 Predictive Relationship between Rainfall and Humanitarian Needs

To illustrate how FIWDs can be designed to hedge against drought induced famine risks in northern Kenya, we explore the predictive relationship between seasonal rains and the prevalence of severely wasted children in each subsequent dry season. For illustrative purposes, we use the cumulative long rains (mm, from March to May) and short rains (mm, from October to December) to characterize seasonal rains in each community. The area average of each of these two seasonal rains is constructed by weighted averaging across 44 communities using communities' mean proportion of severely wasted children as weights. These weighted long rains and short rains represent overall exposure to drought risk in these northern Kenya communities. This area average is the appropriate measure to use to hedge against drought-induced risk since localized droughts can be managed by transferring resources from unaffected areas and so only catastrophic droughts that affect most of the areas need to be transferred.[23]

[23] Correlations coefficients of seasonal rains across these 44 communities vary from 0.16-0.98 for long rains and 0.33-0.99 for short rains.

Season	Long Dry (Hunger Period)	Short Rains	Short Dry (Hunger Period)	Long Rains	Long Dry (Hunger Period)	Short Rains	Short Dry (Hunger Period)
Month	Jun - Sep	Oct - Dec	Jan - Feb	Mar - May	Jun - Jul Aug - Sep	Oct - Dec	Jan - Feb
Current System	Short rains forecast		Short rains assessment Long rains forecast	Appeal	Donor Response Aid delivery Long rains assessment Appeal	Donor Response	Aid delivery
System with FIWDs	Establish FIWD contract to hedge against risk of widespread acute food insecurity during the following short and long dry seasons		First payout triggered at the end of short rains after the realization of cumulative short rains Funding available for Early intervention		Second payout triggered at the end of long rains after the realization of both cumulative long rains and preceding cumulative short rains Funding available for Early intervention		

Figure 3.3 Kenya's Current Drought Emergency Response System

Table 3.1 reports sample district- and overall (basket weighted)-level statistics of the proportion (%) of severely wasted children averaged over short dry (January-February) and long dry (June-September) periods, cumulative long rains (mm), cumulative short rains (mm), monthly average normalized vegetative index (NDVI) – a measure of forage availability for herds – and percentage of communities experiencing failed long rains or short rains, where “failure” reflects cumulative seasonal rainfall more than one standard deviation below the community-specific long-term mean.[24] On average, the proportion of severely wasted children is higher in the long dry period than in the short dry period. Marsabit experienced the highest proportion of wasted children despite its more favorable rainfall. Turkana is typically the most arid district with the lowest mean cumulative short rain and the lowest monthly NDVI. Years when one hundred percent of communities faced failed long rains are observed in all three districts. A high percentage of communities with failed short rains are also observed. On average, 26% of children are severely wasted during long dry seasons and 21% during short dry periods, with the mean cumulative long rain and short rain volumes 218 mm and 136 mm, respectively.

Taking the observed rainfall volume, temporal and spatial effects of rainfall into account, we use two consecutive preceding seasonal rains in predicting the prevalence of severely wasted children in each of the two dry seasons. Seemingly unrelated regression is applied in fitting these two relationships using six years of 44-community-basket weighted variables available from the 2000-2005 ALRMP data.

[24] Proportion of severely wasted children (% MUACZ<-2) statistics are from 2000-2005, rainfall statistics are from 1961-2006 and normalized vegetative index (NDVI) statistics are from 1990-2005.

Table 3.1 Sample Statistics of Weather and Proportion of Severely Wasted Children

District	Statistics	Short Dry (% MUAC z<-2)	Long Dry (% MUAC z<-2)	Long Rain (mm)	Short Rain (mm)	Failed Long Rain (%)	Failed Short Rain (%)	NDVI
Marsabit	Mean	0.20	0.29	223	162	14	15	0.32
9 communities	S.D.	0.11	0.04	86	70	30	27	0.15
	Minimum	0.00	0.24	53	8	0	0	0.09
	Maximum	0.31	0.35	454	327	100	100	0.69
Samburu	Mean	0.16	0.22	214	144	15	15	0.29
14 communities	S.D.	0.07	0.11	84	68	27	27	0.12
	Minimum	0.09	0.07	62	12	0	0	0.05
	Maximum	0.26	0.38	417	313	100	93	0.64
Turkana	Mean	0.25	0.26	217	119	16	10	0.22
21 communities	S.D.	0.09	0.12	59	66	26	17	0.12
	Minimum	0.14	0.10	78	20	0	0	0.05
	Maximum	0.34	0.46	317	395	100	67	0.62
All (weighted)	Mean	0.21	0.26	218	136	15	13	0.26
44 communities	S.D.	0.09	0.10	69	62	25	21	0.14
	Minimum	0.00	0.07	66	15	0	0	0.05
	Maximum	0.34	0.46	371	344	100	82	0.69

Note: 44 Communities are weighted using their mean proportion of children with MUAC z<-2 in dry seasons.

The estimated forecasting model of basket weighted proportion of severely wasted children in the long dry season was[25]

$$\ln(F_{LD})_t = \underset{(2.34)}{3.607} - \underset{(0.13)}{0.619}\ln(LR)_t - \underset{(0.35)}{0.177}\ln(SR_{-1})_t - \underset{(0.07)}{0.224}\ln(AID_{LD})_t + \varepsilon_t \qquad (3.8)$$

where F_{LD} is the proportion (%) of severely wasted children averaged over the long dry season (June-September), LR is the cumulative long rains (mm), SR_{-1} is the immediate leading cumulative short rains (mm) of the preceding year, AID_{LD} represents the basket weighted average of communities' mean quantity food aid (kg) received per household per year calculated from October of the preceding year to September (the end of long dry period), and t represents time in years. Similarly, the forecasting model for proportion of severely wasted children in the short dry period was

$$\ln(F_{SD})_t = \underset{(2.60)}{5.28} - \underset{(0.247)}{0.248}\ln(LR_{-1})_t - \underset{(0.52)}{1.113}\ln(SR_{-1})_t - \underset{(0.15)}{0.119}\ln(AID_{SD})_t + \varepsilon_t \qquad (3.9)$$

where F_{SD} represents the proportion (%) of severely malnourished children averaged over short dry season (January-February), LR_{-1} is the cumulative long rains (mm) of the preceding year, and AID_{SD} is the mean quantity food aid (kg) received per household per year calculated from March of the preceding year to February (the end of short dry period). The r^2 for these regressions are 0.753 for long dry model and 0.563 for the short dry season.

These model specifications were used in this illustrative case for a variety of reasons. First, the basket weighted average covariates represent the weighted aggregate of the overall exposure to drought-induced famine risks in these

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[25] Standard errors are reported in the parentheses.

communities under study. Second, the coefficients are consistent with our priors about the relationship between rainfall and malnutrition. Third, the estimated parameters showed reasonable statistical significance, even though the number of observations was very low. Fourth, the model selected was the best of many models examined. Finally, although our data were obtained from a large number of monthly observations we were limited in time to annual counts of the proportion of wasted community children to six annual measures. This is a data limitation that will be overcome in time,[26] but for the purely illustrative purposes of this paper and the FIWD concepts and pricing methods it introduces, there is no better measure to directly predict prevalence and degree of food insecurity and we would rather err on the side of precision.

We should also explain that food aid variables were included in these forecasting models purely to control for (i) non-weather effects (e.g., disease, conflict) that matter to the variability of the proportion of severely wasted community children, and (ii) preprogrammed food aid flows (e.g., school feeding and other non-emergency food aid as well as food aid resulting from prior years' appeals).[27] The predictive relationships between the two preceding seasonal rains and the prevalence of severely wasted children conditional on an ex-ante expectation of a food aid pipeline can now be used to develop a parametric famine index for FIWDs.

According to (3.8), a 1% increase in the basket weighed long rains will decrease the overall proportion of severely wasted children by 0.619%, whereas a 1% increase in short rains will decrease the malnutrition proportion by 0.177%. Clearly the influence of the long rains is more indicative of wasting in the long dry season

[26] Phase two of the ALRMP project from 2005 onward continues to collect data from these communities.

[27] The weighted average yearly food aid variables used are not statistically determined by the prevalence of severely malnourished children in dry seasons. Thus reverse causality does not appear to be an issue in these data.

than the prior fall short rains. And as expected, (3.9) also suggests that the preceding short rains seem to have a more significant impact on malnutrition status in the short dry period compared to the preceding long rains. Nonetheless with significantly different impacts, two preceding seasonal rains are both critical predictors of short dry seasons' prevalence of severely wasted children. The combination of these two rain events characterizes a joint weather-event trigger for derivative contracts.

3.5.3 Designing Famine Index Weather Derivatives for Northern Kenya

Using forecasted proportion of severely wasted children as an indicator of acute food insecurity, the famine index derived from the predictive relationship in (3.8) for the long dry season is thus $F_{LD} = 36.845 LR^{-0.619} SR_{-1}^{-0.177} AID_{LD}^{-0.224}$. Holding the prevalence of child malnutrition constant at F_{LD}^{*}, and incorporating the food aid variable based on ex-ante expectation of $\overline{AID}_{LD}$ (40 kgs/household food aid in the pre-existing pipeline[28]) into the intercept, we use

$$LR^{*}(SR_{-1}(F_{LD}^{*})) = \left[\frac{36.845\overline{AID}_{LD}^{-0.224} SR_{-1}^{-0.177}}{F_{LD}^{*}}\right]^{\frac{1}{0.619}} \tag{3.10}$$

to obtain the conditional trigger of cumulative long rains conditional upon the already observed outcome of the preceding cumulative short rains. Critically important is the inclusion of the famine index, in term of proportion of wasted children, F_{LD}^{*}, not as an outcome, but as a policy variable. Here (3.10) represents what we will refer to as an iso-food insecurity index curve, as depicted in Figure 3.4. This is similar to an isoquant in classical production economics. At a particular level of expected aid

[28] The level of food aid at 40 kgs/household /year, used here for illustrative purpose, is approximately one standard deviation below the 2000-2005 means.

delivery, this curve shows the loci of strike or trigger long rain levels, $LR^*(SR_{-1}(F_{LD}^*))$, given an observed preceding SR_{-1} that probabilistically leads to a level of prevalence of severely wasted children F_{LD}^* in the long dry season. It thus can serve as an early warning mechanism for slow onset food crisis.

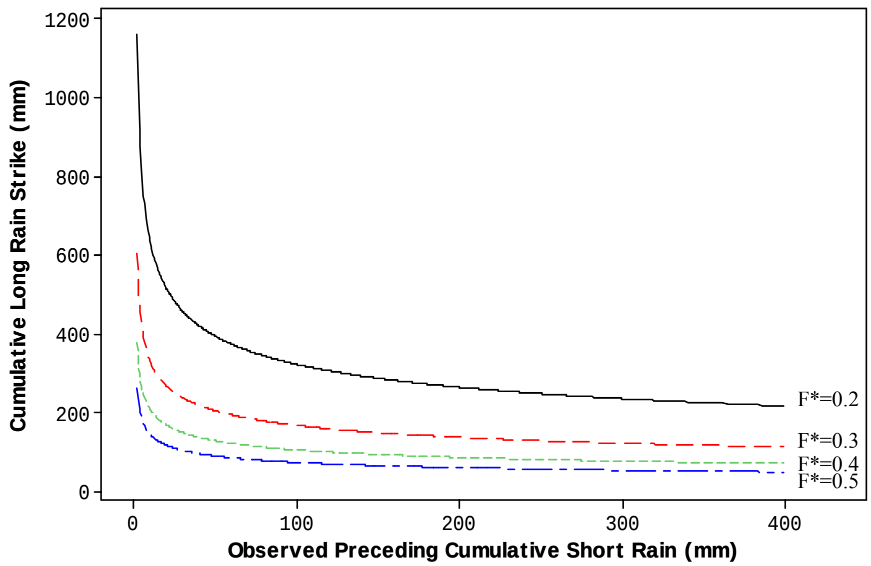

Figure 3.4 Iso-Food Insecurity Index Relations for Hedging Against Levels of Prevalence of Severely Wasted Children (F^*)

The critical calculus is $\dfrac{\partial LR^*(SR_{-1}(F_{LD}^*))}{\partial F_{LD}^*} < 0$, and so as the chosen level of prevalence of severely wasted children to hedge against, F_{LD}^*, increases, the long rain trigger decreases. This is depicted in Figure 4 as a downward shift in the iso-food insecurity index curve. In addition, $\dfrac{\partial LR^*(SR_{-1}(F_{LD}^*))}{\partial SR_{-1}} < 0$ indicates that as the observed preceding short rain increases, the long rain strike required to hedge against a given level of prevalence of severely wasted children F_{LD}^* is lower. Thus the long rain strike $LR^*(SR_{-1}(F_{LD}^*))$ is determined jointly by the random outcome in the preceding short rains and the chosen level of F_{LD}^*.

The meaning of F_{LD}^* is critical. Like a deductible in conventional insurance, the choice of F_{LD}^* represents the level of food insecurity for which the government or operational agencies can provide assistance using existing resources (food and cash) but above which will need additional resources. Thus if $F_{LD}^* = 0.3$, the iso-food insecurity index curve determines the boundary of short and long rain combinations, below which prevalence of wasted children $F_{LD}^* > 0.3$ could arise probabilistically. In other words, to ensure that cash for emergency food relief is available for early prevention of the predicted prevalence of severe child malnutrition beyond a pre-specified level F_{LD}^* in the long dry season, this model is equivalent to a random strike model with the indemnity payout at the end of the long rain established by $\Pi = Max[C(LR^*(SR_{-1}(F_{LD}^*)) - LR),0]$. Here, $C(\cdot)$ links the particular prevalence and severity of child wasting resulting from a long rain shortfall to the appropriate dollar amount of humanitarian assistance needs and the long rain strike $LR^*(SR_{-1}(F_{LD}^*))$ below which the contract triggers a payout. Importantly, its determination is based on the realization of the preceding cumulative short rain.[29,30]

For illustrative purposes, we consider a derivative contract written before the short rains period (e.g., in September) to hedge against the potential widespread food insecurity event in the short dry (e.g., during January-February of the following year) as well as long dry (June-September of the following year) seasons. The specific instruments we investigate first are index insurance contracts with

$$\Pi_{SD(t)} = \$1{,}000{,}000 \cdot 1_{(SR \le 65mm)} \tag{3.11}$$

[29] Random strike models are useful when there is a causal intertemporal relationship between one weather event and a subsequent event on a particular outcome. See Turvey et al. (2006) for an example of a random strike price in a different context.

[30] A similar procedure could be used to derive an indemnity structure for hedging against prevalence of widespread child wasting in the short dry season based on a random short rain strike conditional on the observed preceding long rain. However, our investigation indicates that prevalence is established relative to the short rains.

$$\Pi_{LD(T)} = \$1{,}000{,}000 \cdot Max\left((LR^*(SR_{-1}(F_{LD}^*)) - LR)^x, 0\right) \tag{3.12}$$

$$\Pi_T = e^{r(T-t)} \cdot \Pi_{SD(t)} + \Pi_{LD(T)} \tag{3.13}$$

where (3.11) is a binary option with an indemnity paid out at the end of short rain season (e.g., in January) if there is a severe shortfall in the cumulative short rain below 65mm. This indemnity structure takes into account the need for an immediate cash payout to finance early intervention should weak short rains leads to a catastrophic food crisis in the short dry period.[31]

Equation (3.12) is the main indemnity structure and the primary vehicle for the famine insurance product for hedging widespread food crisis in the critical long dry season. It holds a tick \$1,000,000 for every millimeter of long rain falling below the strike, $LR^*(SR_{-1}(F_{LD}^*))$. The payoff may be raised to the power *x*, which increases this payoff fractionally as the long rain shortfall increases. The idea here is that there is a non-linear relationship between drought and prevalence of child malnutrition with the risk of famine increasing convexly in respect to decreases in rainfall. The total indemnity payoff at the end of the contract is thus provided in (3.13) by adding the value of the short dry indemnity paid immediately after short rain season adjusted for time value by discount factor *r*, and the long dry indemnity paid at the end of long rain season, which is assumed to be the end of the contract. A cap ($\overline{\Pi} \geq 0$) on the maximum indemnity payout can be applied in order to limit the insurer's losses so that the total payout at the end of the contract (*T*) becomes

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[31] The short rain strike of 65mm is obtained in similar fashion to that of $LR^*(SR_{-1}(F_{LD}^*))$. Specifically, the short rain strike conditional on the preceding long rain outcome observed before the start of the contract can be written as $SR^*(LR_{-1}(F_{SD}^*)) = \left[\dfrac{196.429\overline{AID}_{SD}^{-0.119} LR_{-1}^{-0.248}}{F_{SD}^*}\right]^{\frac{1}{1.113}}$.

The strike $SR^*(LR_{-1}(F_{SD}^*)) = 65$ mm is based on the expectation of $\overline{AID}_{SD} = 75$ kilograms per household per year, $F_{SD}^* = 0.3$ and an average long rain of 210 mm.

$$\Pi_{capped} = Min\left(e^{r(T-t)} \cdot \Pi_{SD(t)} + \Pi_{LD(T)}, \overline{\Pi}\right) \tag{3.14}$$

Second, we consider the simple one year, zero-coupon famine bond with principal P, rate of required return r and an indemnity payout structure Π_{capped} described in (14) and capped at $\delta\%$ of the principal. We then price this based on

$$B(0,T) = e^{-rT} \cdot [P - \Pi_{capped}] \quad \text{where} \quad \overline{\Pi} = \delta P. \tag{3.15}$$

The famine bond is initially sold at a discount. The bondholder's realized annual return if the insurance indemnity is not triggered is therefore the difference between the principal and the purchased bond price. The structure of these famine indexed weather derivative contracts are shown in Figure 3.3. The next section analyses the expected payoffs from contracts with various combinations of these factors.

3.5.4 Pricing Famine Index Weather Derivatives

We present the pricing results from the insurance product first and the famine bond second. As discussed previously, the two are related in that it is the indemnity structure of the weather insurance product that determines the discount on the famine bond.

Two methods are used as a matter of comparison. In the top panel of Tables 3.2, 3.3 and 3.5, the results are derived using a burn rate approach, which is based on the actual historical outcomes from 46 years of rainfall data. The bottom panels are based on 50,000 Monte Carlo simulations using the best fit distributions for basket weighted cumulative short rain (gamma(8.0525,21.279)) and cumulative long rain (lognormal(3357.6,68.56)).[32] The long rain strike used throughout these results is based on a minimal level of food aid delivery of 40 kilograms per household per year, about 75% standard deviation below its 2000-2005 mean. The insurance indemnity payouts are based simply on the parameter $x = 1$, so payouts are linearly related to rain shortfall relative to the trigger level. The tables present the expected indemnity payoff for index insurance contracts in order to reflect the value of the products as determined by the distribution of short and then long precipitation risk. Actuarial fair premiums can thus be derived easily by discounting these expected payoffs with an appropriate discount rate.

For the insurance contracts for hedging against a given level of child wasting prevalence F^* defined from 0.2 to 0.5 for each column, the expected long rain strike decreases from 308.6 to 70.2 millimeters, reflecting the fact that as the level of malnutrition prevalence one want to hedge against is higher, the likelihood and magnitude of contract payout is thus lower. The expected payoffs in long dry season (contingent on conditional long rain strike) therefore decrease substantially as the level of F^* increases. They range from about \$97.2 million and \$95.5 million for $F^* = 0.2$, to \$3,538 and \$388,426 for the burn and Monte Carlo estimates at the higher level of $F^* = 0.5$ with much rarer trigger probability. According to the 46-year historical data, contract covering $F^* = 0.5$ made one payout in the year 2000, the worst drought in the past forty years of Kenya. On the contrary, the fact that the contract covering $F^* = 0.2$ triggered payouts in 39 out of 46 years is expected, as the average proportion of severely wasted community children in these particular districts of Kenya is already as high as 0.26 in the long dry season. Two payouts were made in 1997 and 2000 at $F^* = 0.45$ and $F^* = 0.4$, implying a frequency of one in 23 years.

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[32] Distributions are written as Gamma(α, β) - where $\alpha > 0$ determines shape or skewness and $\beta > 0$ determines scale or width of the distribution, and Lognormal(μ, σ) with parameters for mean and variance, respectively.

The contingent claim on short rains failure occurs only under severe conditions (specifically in 1970, 1997 and 2005, coinciding with the historical record of devastating droughts due to short rains failure). The payoff of $65,217 based on historical measures compares to $102,780 using Monte Carlo, indicating that the best fit distribution is skewed more negatively than history might have recorded. The total expected payoffs from contingencies on both short and long rain range from $97.3 millions to $70,929 using the burn approach and $95.7 millions to $494,634 using the Monte Carlo approach.

The range of payoffs is much higher using the Monte Carlo approach. The differences between the burn approach and the Monte Carlo approach are due to the sampling frame. The burn approach assumes that all possible outcomes are contained within the history of the sample while the Monte Carlo approach, driven by a defined distribution, assumes the existence of rarer events on the downside that were not realized during the historical period strata. Especially, at $F^* = 0.5$ with only one payout triggered historically, the 50,000 iteration Monte Carlo approach would have sampled more possible severe outcomes, as rare as they might be.

The capped insurance results are provided in Table 3.3. The caps – ceiling of covering insurance payout that limits the insurer's loss – used were approximately 70% of the largest historical payoff. The capped products are remarkably similar with expected payoffs (and standard deviations) between the burn and Monte Carlo approaches very close. Under the Monte Carlo approach, the effects of the caps reduced total expected payoffs from $97.5 million to $94.2 million for $F^* = 0.2$, and from $494,638 to $93,282 for $F^* = 0.5$. More generally as the cap increases, so too would the range of payouts and hence the cost of the insurance.

Table 3.2 Weather Index Insurance Expected Payoff Statistics, 1961-2006

Famine Trigger (F*)	0.2	0.25	0.3	0.35	0.4	0.45	0.5
Strike SR* (mm)	65	65	65	65	65	65	65
Historical Burn Rate							
Expected Strike LR* (mm)	309	215	160	125	101	83	70
Expected SD Payoff ($)	65,217	65,217	65,217	65,217	65,217	65,217	65,217
Expected LD Payoff ($)	97,220,597	29,505,197	10,353,626	4,055,296	1,425,886	600,631	3,532
Expected Total Payoff ($)	97,287,994	29,572,594	10,421,023	4,122,693	1,493,283	668,028	70,929
S.D. Total Payoff ($)	81,419,233	49,554,422	27,145,007	13,906,329	6,969,875	3,023,025	272,219
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	374,106,609	205,193,020	113,205,263	69,259,487	39,104,762	17,402,449	1,195,889
SD Triggered Years	3	3	3	3	3	3	3
LD Triggered Years	39	23	10	5	2	2	1
Monte Carlo Simulation							
Expected Strike LR* (mm)	308	215	160	125	101	83	70
Expected SD Payoff ($)	102,780	102,780	102,780	102,780	102,780	102,780	102,780
Expected LD Payoff ($)	95,571,430	28,752,950	8,916,012	3,218,886	1,350,931	690,477	388,426
Expected Total Payoff ($)	95,677,680	28,859,160	9,022,220	3,325,094	1,457,118	796,706	494,634
S.D. Total Payoff ($)	76,621,900	45,106,260	24,514,640	14,297,660	8,521,659	5,823,947	4,233,706
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	996,512,400	648,651,000	542,513,000	599,369,000	432,394,500	194,205,900	116,622,200

Note: The expected total payoffs are calculated at the end of the contract, where the expected SD payoffs are brought forward using 8% rate of return. Actuarial fair premium can be calculated by discounting the expected total payoff with the appropriate discount rate.

The one-year catastrophe bond discounts are provided in Table 3.4 for various combinations of caps as a percent of principal and various required rates of return – the difference of which from the risk-free rate represents risk premiums investors required. These rates are chosen such that they reasonably represent spreads required by investors in the existing cat bond markets (according to Froot 1999). The values in Table 3.4 indicate the retail price of a bond per dollar of principal. The total annual return realized by the bondholder will always be higher than the required rate of return if the triggering widespread acute food insecurity event does not occur. The difference between the two thus represents an additional premium required associated with the catastrophic famine risk. For example, a famine bond covering prevalence of severe wasting of $F^* = 0.3$ with a required rate of return of 8% and cap at 30% is priced at \$0.8787 and will pay \$1 principal one year later should the famine condition not be triggered. Thus the total return realized by the investor if a critical drought event is not triggered[33] is 12.13%, which can be interpreted as an additional 4.13% premium associated with the famine risk contingency and above the risk premium required for other sources of risk e.g., default risk, interest rate term structure risk, etc. However, if triggered, principal payment decreases to as little as \$0.3 for a loss of 57.8%.

In general, for a given cap level and required rate of return, the famine bond prices decrease with the level of malnutrition prevalence to be insured against, since the lower F^* trigger means that the bond has higher probability to trigger payout and thus is more risky. Similarly, famine bond prices decrease as the cap level increases, as the smaller proportion of repaid principal if the bond triggers translates into the higher risk of loss. And finally, it is straightforward to see that the bond prices decrease as the required rates of return increase.

[33] Equivalently, the total return of a famine bond can be interpreted as a 7.18% spread over one-year LIBOR rate of 5.12%. LIBOR rate is as of September 11, 2007.

Table 3.3 Capped Weather Index Insurance Expected Payoff Statistics, 1961-2006

Famine Trigger (F*)	0.2	0.25	0.3	0.35	0.4	0.45	0.5
Strike SR* (mm)	65	65	65	65	65	65	65
Cap (70% of Historical Max.)	260,000,000	140,000,000	80,000,000	50,000,000	28,000,000	10,000,000	800,000
Historical Burn Rate							
Expected Strike LR* (mm)	309	215	160	125	101	83	70
Expected Total Payoff ($)	93,989,039	27,253,505	9,070,036	3,701,586	1,251,876	479,714	52,174
S.D. Total Payoff ($)	72,109,066	42,354,305	22,431,866	12,060,865	5,718,127	2,063,170	199,710
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	260,000,000	140,000,000	80,000,000	50,000,000	28,000,000	10,000,000	800,000
Monte Carlo Simulation							
Expected Strike LR* (mm)	308	215	160	125	101	83	70
Expected Total Payoff ($)	94,215,120	27,636,790	8,035,131	2,673,187	972,646	321,917	93,282
S.D. Total Payoff ($)	71,489,720	40,392,290	19,479,810	9,651,412	4,457,400	1,445,366	256,701
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	260,000,000	140,000,000	80,000,000	50,000,000	28,000,000	10,000,000	800,000

Table 3.4 Zero-Coupon Famine Bond Prices for Different Bond Specifications*

Required Return	Cap (%Face)	Famine Trigger (F*)						
		0.2	0.25	0.3	0.35	0.4	0.45	0.5
6%	30%	0.708	0.826	0.896	0.922	0.933	0.937	0.938
	50%	0.571	0.775	0.879	0.916	0.931	0.936	0.938
	70%	0.450	0.739	0.870	0.913	0.930	0.935	0.937
8%	30%	0.696	0.812	0.879	0.904	0.914	0.918	0.920
	50%	0.561	0.761	0.862	0.898	0.912	0.917	0.919
	70%	0.443	0.724	0.853	0.895	0.911	0.917	0.919
10%	30%	0.682	0.796	0.861	0.886	0.896	0.900	0.901
	50%	0.550	0.745	0.845	0.880	0.894	0.899	0.901
	70%	0.434	0.709	0.836	0.878	0.893	0.898	0.901
12%	30%	0.668	0.780	0.844	0.869	0.878	0.882	0.883
	50%	0.539	0.731	0.828	0.863	0.876	0.881	0.883
	70%	0.425	0.695	0.819	0.860	0.875	0.881	0.883

Note: Prices are based on 50,000 Monte Carlo simulations using best fit distributions

3.5.5 Using Famine Indexed Weather Derivatives to Improve Drought Emergency Response

The risk-transferring potential of the FIWD contracts proposed here vary greatly with the frequency of the extreme events as well as their degree of catastrophe. For example, as shown in Table 3.3, capped weather index insurance covering severe wasting prevalence $F^* = 0.2$ results in a prohibitive premium with expected payoff of \$93.9 million. The contract triggers payout in 39 of 46 years due to the fact that the average proportion of severely wasting condition in northern Kenya is already as high as 0.26 in the long dry season. But the results in Table 3 further suggest that early intervention at $F^* = 0.3$ or higher (with the frequency of 10 in 46 years) may feasibly be financed using famine index insurance. The insurance contract that covers up to \$80 million requires a premium with expected payoff of approximately \$8 million. Alternatively, intervention triggered by $F^* = 0.4$ or more (occurring in 1-2 of 46 years) may also feasibly be financed using famine bonds. At the required rate of return of 8% and with a 50% cap, famine bonds covering $F^* = 0.4$, 0.45 or 0.5 can be issued at the total rate of return of 8.82%, 8.3% and 8.09% respectively.

While these derivative products can be used to finance emergency response to catastrophic drought risk, coordinating them with other sources of humanitarian funding and the country's existing drought contingency resources may further enhance the potential and cost effectiveness of the early intervention. Integrated risk financing ideas proposed in Hess and Syroka (2005) and Hess et al. (2006) for Ethiopia and Malawi can be similarly illustrated in the context of drought emergency response financing for arid northern Kenya. Suppose that early emergency response is crucial if $F^* = 0.25$. The financial exposure associated with the emergency intervention costs can be first layered by their frequency and level of catastrophe. The instruments covering various layers of these exposures, characterized by different conditional long rains strike and cap levels are derived and shown in Table 3.5.

Table 3.5 Layering Financial Exposure in Providing Emergency Intervention to Drought Events Using Triggering Level of Prevalence of Child Malnutrition of 0.25

Famine Trigger (F*)	0.25	0.25	0.25	0.25
Strike SR* (mm)	65	65	65	65
Layering Strike LR*	LR*	LR*-30	LR*-60	LR*-120
Cap for LR Payoff	30,000,000	30,000,000	60,000,000	100,000,000
Historical Burn Rate				
Expected Strike LR* (mm)	215	185	155	95
Expected Total Payoff ($)	11,671,814	7,146,556	7,301,997	3,519,623
S.D. Total Payoff ($)	13,576,351	12,150,113	18,278,614	15,399,052
Minimum Payoff ($)	0	0	0	0
Maximum Payoff ($)	30,000,000	30,000,000	60,000,000	85,193,020
Monte Carlo Simulation				
Expected Strike LR* (mm)	215	185	155	95
Expected Total Payoff ($)	12,049,830	7,849,441	6,994,606	1,995,035
S.D. Total Payoff ($)	13,838,810	12,357,140	16,692,620	10,344,390
Minimum Payoff ($)	0	0	0	0
Maximum Payoff ($)	30,000,000	30,000,000	60,000,000	100,000,000

For illustrative purposes, financial exposure can be disaggregated into four layers and can then be managed sequentially by (i) government reserves or pre-established contingency funds, (ii) contingent debt/grants, (iii) famine indexed insurance and (iv) famine bonds – which now becomes feasible for the layer of a 4-in-46 year loss event (or with approximately 8.7% probability of occurrence per year). The first layer covers the most frequent loss exposure (23 in 46 years event) and up to $30 million. This layer covers the operational costs on the most recurrent but relatively minor losses, e.g., local droughts occurring almost every two years, which lead to an expected loss of as high as $11.67 million. The second contract covers the loss beyond the first contingency layer, up to another $30 million. Since this layer of loss still occurs with relatively high probability, it may be too costly for any commercial risk transfer products and thus may be appropriately financed by a contingent debt or grant from development facilities available from many international financial institutions (e.g., World Bank). The expected loss of $7.1 million will be financed in this layer.

The major catastrophic losses requiring an extensive emergency response can then be financed using index insurance or a famine (cat) bond. However, the probability of occurrence of the next layer of risk may still be too high (8 in 46 year event) to be appropriate for a cat bond. A weather index insurance contract may first be used to cover this immediate layer of losses up to $60 million, with a premium representing expected payoff of $7.3 million. Finally, a famine bond contract can then be designed for the last, low-probability-catastrophic-loss layer, up to $100 million in humanitarian budgetary needs. The donor appeals process can then resume for any remaining costs not covered by these financing mechanism, e.g., costs exceeding $100 million or extra costs not fully captured in the derivative contracts. But with an initial, substantial funding layer in place and available for immediate payout, both the overall costs and the time pressures should be reduced, making the appeals process a viable vehicle for topping up pipelines begun through these other risk management instruments.

It is worth noting that the total drought risk financing costs will vary with the layering strategy as well as with the combinations of instruments used. The main idea, therefore, is that contracts based on forecasted prevalence and severity of food insecurity can be designed and used as a trigger mechanism to coordinate multiple prospective sources of emergency funding in order to increase cost effectiveness and timely response to drought-induced humanitarian disasters.

3.6 Discussion and Implications

There is no general approach for the design and pricing of famine indexed weather derivative contracts. This paper presents the first attempt. The results from our illustrative case from northern Kenya are of course specific to the assumptions we made and replicable only over the equivalent distributions of climate and human ecology. It is therefore best to focus on the principles involved and not on the specific numerical estimates. These principles and their numerical illustrations are nonetheless both important and exciting.

Our objective was to develop a weather-based famine insurance product that could be used by governments, operational agencies or NGOs to enhance the timeliness and reliability of funding for emergency intervention to catastrophic but slow-onset droughts. We proposed a general structure for famine indexed weather derivatives, but emphasize two common yet critical characteristics. First, weather variables or event trigger(s) need to be indexed to a forecasted degree of prevalence and severity of food crisis so that it can serve as both an early warning to trigger early intervention and to provide the cash necessary for such intervention. Second, as delayed humanitarian assistance is costly, even deadly, contractual payouts need to be structured to cover potential emergency response over all possible vulnerable periods in the year. FIWDs with these two features can be integrated with existing humanitarian funding facilities.

Though using the best measures available given the problem identified, the FIWDs designed for northern Kenya should be taken as an illustrative case only and require further investigation if considered for real applications, for a variety of reasons. First, though derivative prices are based on 46 years of high-quality rainfall data, the predictive relationship between weather and food insecurity is derived from only six years' available household data. It is therefore critical to re-estimate the relationships with additional data in order to minimize potential basis risk. Second, the suitability of communities' proportion of severely wasted children (measured by MUAC z-score <-2) as a proxy for severe human suffering relies on an accurate and continued data collection processes at the community level. The principles and results generated in this article emphasize the importance of and the need for improving data collection and standardization, which can strengthen the potential and feasibility of famine indexed weather derivatives in the near future.

CHAPTER 4

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

4.1 Introduction

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

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

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

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

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

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

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

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

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

The remainder of the paper is organized as follows. Section 4.2 describes the northern Kenya context. Section 4.3 explains the livestock mortality and remote sensing vegetation data available. Section 4.4 details the IBLI contract design, the construction of key variables and the estimation methods employed. Section 4.5 reports and evaluates the performance of the estimated livestock mortality models that underpin the IBLI contract. Section 4.6 discusses contract pricing and risk exposure. Section 4.7 concludes with a discussion of implementation challenges for this and similar index insurance products.

4.2 The Northern Kenya Context

The more than three million people who occupy northern Kenya's arid and semi arid lands (ASALs) depend overwhelmingly on livestock, which represent the vast majority of household wealth and account for more than two-thirds of average income. Livestock mortality is therefore perhaps the most serious economic risk these pastoralist households face. The importance of livestock mortality risk management for pastoralists is amplified by the apparent presence of poverty traps in east African pastoral systems, characterized by multiple herd size equilibria such that losses beyond a critical threshold – typically 8-16 tropical livestock units (TLUs) – tend to tip a household into collapse into destitution (McPeak and Barrett, 2001; Lybbert et al., 2004; Barrett et al., 2006). Indeed, uninsured risk appears a primary cause of the existence of poverty traps among east African pastoralists (Santos and Barrett 2008).

Most livestock mortality is associated with severe drought. In the past 100 years, northern Kenya recorded 28 major droughts, 4 of which occurred in the last 10 years (Adow 2008). The climate is generally characterized by bimodal rainfall with short rains falling in October – December, followed by a short dry period from January-February. The long rain – long dry spell runs March-May and June-September, respectively. Pastoralists commonly pair rainy and dry seasons, for example observing that failure of the long rains results in large herd losses at the end of the following dry season.

Pastoralist households commonly manage livestock mortality risk ex ante, primarily through animal husbandry practices, in particular nomadic or transhumant migration in response to spatiotemporal variability in forage and water availability. When pastoralists suffer herd losses, there exist social insurance arrangements that provide informal interhousehold transfers of a breeding cow; but these schemes cover less than ten percent of household losses, on average, do not include everyone and are generally perceived as in decline (Lybbert et al. 2004; Santos and Barrett 2008; Huysentruyt et al. 2009). Some households can draw on cash savings and/or informal credit from family or friends to purchase animals to restock a herd after losses. But the vast majority of intertemporal variability in herd sizes is biologically regulated, due to births and deaths (McPeak and Barrett 2001; Lybbert et al. 2004). Thus most livestock mortality risk remains uninsured at household level.

Meanwhile, most herd losses occur in droughts as covariate shocks affecting many households at once, sparking a humanitarian emergency. The resulting large-scale catastrophe induces emergency response by the government, donors and international agencies, commonly in the form of food aid. As the cost and frequency of emergency response in the region has grown, however, mounting dissatisfaction with food aid-based risk transfer has prompted exploration for more comprehensive and effective means of livestock mortality and drought risk management, including the development of viable financial risk transfer products. The most recent parliamentary campaign in Kenya included widespread, highly publicized promises by prominent politicians to develop livestock insurance for the northern Kenyan ASAL.

4.3 Data Description

The northern Kenya IBLI contract is designed using combination of household-level livestock mortality data collected monthly since 1996 in various locations by the Government of Kenya's Arid Land Resource Management Project (ALRMP, http://www.aridland.go.ke/) and dekadal (every 10 days) NDVI data computed reliable at high spatial resolution (8 km^2 grids) and consistent quality from satellite-based

Advanced Very High Resolution Radiometer (AVHRR) measurement since 1981.[34] We also employ household-level panel data collected quarterly by the USAID Global Livestock Collaborative Research Support Program Pastoral Risk Management (PARIMA) project (Barrett et al. 2008) to analyze the IBLI contract's performance out of sample. The use of NDVI data is uncommon in index insurance design, especially in the developing world; the use of household-level panel data in contract design is, to the best of our knowledge, unique.

We focus specifically on what was until recently Marsabit District, where the ALRMP data are most complete and reliable, offering monthly household survey data from January 2000 to January 2008 in 7 locations in Marsabit[35] It is thus possible to construct location-specific seasonal herd mortality rate for each location for long rain-long dry seasons (the period from March-September) and short rain-short dry seasons (from October-February), providing a minimally adequate sample size of 112 location-and-season specific observations.

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

$$M_{ls} \equiv \frac{\sum_{m \in s} \overline{H}_{mort,m}}{\underset{m \in s}{Max}\left(\overline{H}_{beg,m}\right)} \tag{4.1}$$

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

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

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

There is considerable heterogeneity within the Marsabit region, as reflected in Table 4.1. We therefore performed statistical cluster analysis to identify locations with similar characteristics, generating two distinct clusters of three to four locations each (Figure 4.1). The Chalbi cluster is characterized by more arid climate, camel- and smallstock (i.e., goats and sheep) based pastoralism by the Gabra and Borana ethnic groups. The Laisamis cluster enjoys slightly higher (and more variable rainfall) and forage, hence its greater reliance on cattle and smallstock by the Samburu and Rendille peoples.

Table 4.2 reports mortality rates by location.[36] Locations in Chalbi (Laisamis) cluster experienced relatively higher and more variable mortality rate during the SRSD (LRLD) season. The differences are statistically significant between seasons within each cluster and between clusters within each season. Mortality rates are highly correlated within the same cluster (0.80-0.95), while correlations between clusters are less. As Figure 4.2 shows, the 2000 and 2005-06 years exhibited the highest mortality losses during this period. Mortality rates are low – uniformly less than 20%, typically

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

less than 10% – outside of these severe drought periods. The frequency of area average mortality rates exceeding 10% is approximately 33% (a 1-in-3 year event) for both Chalbi and Laisamis. However, the probability of herd mortality exceeding 20% (30%) is approximately 15% (9%) for Chalbi in contrast to 19% (14%) for Laisamis, while the proportion of extreme herd mortality exceeding 50% is approximately 6% for Chalbi in contrast to only 2% for Laisamis.

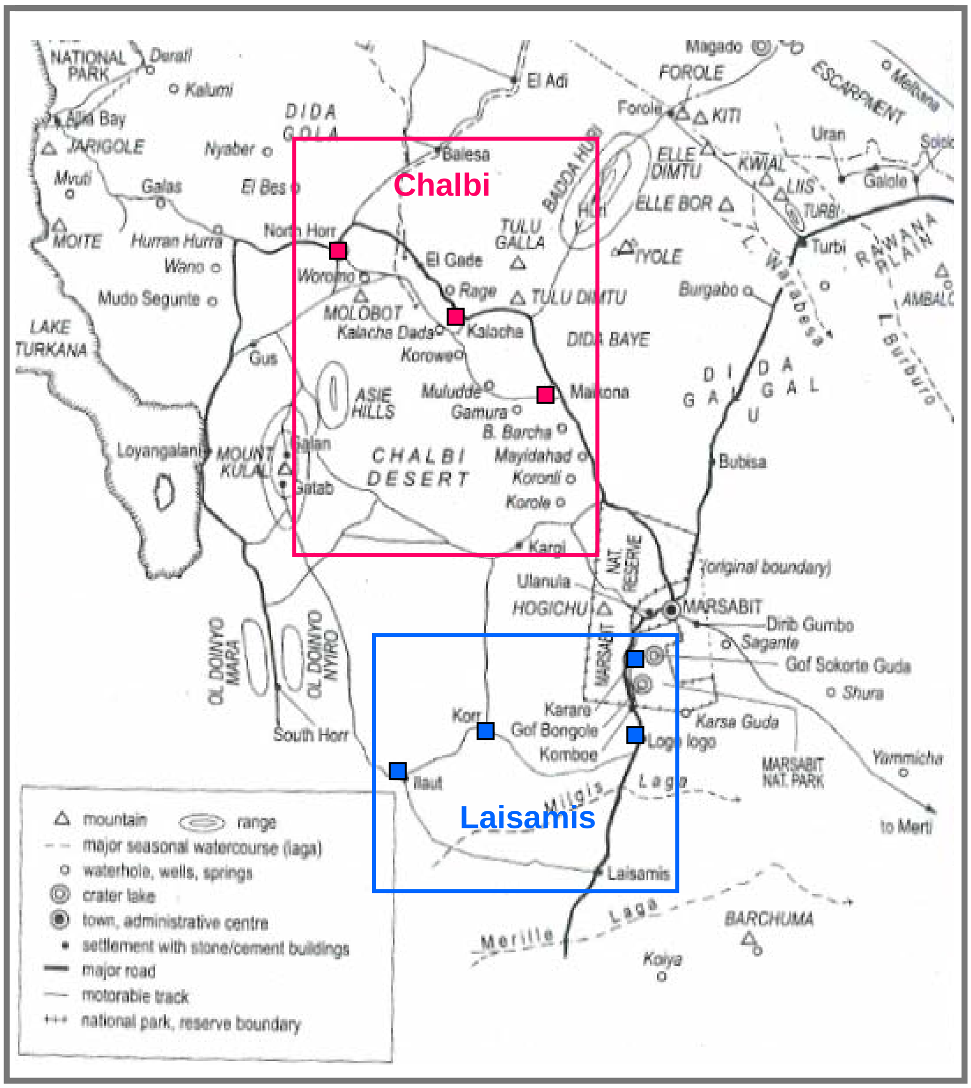

Figure 4.1 Clustered Sites in Marsabit, Northern Kenya

Table 4.1 Descriptive Statistics, by Cluster

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

Table 4.2 Seasonal Herd Mortality Rates, 2000-2008

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

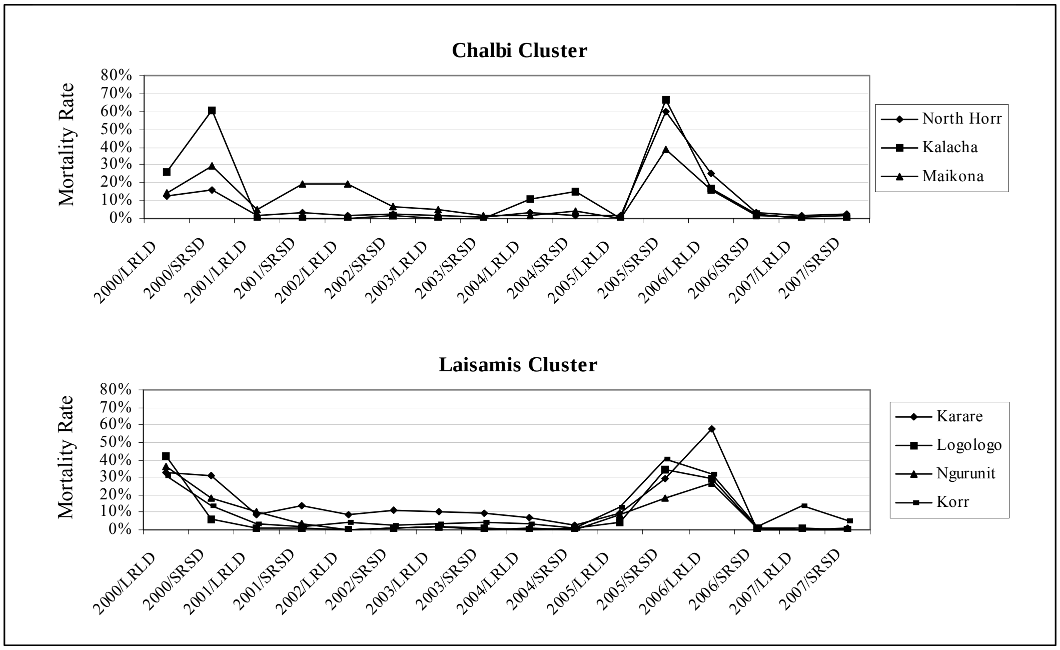

Figure 4.2 Seasonal TLU Mortality Rate by Clusters

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

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

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

The second reason is practical. Kenya does not have longstanding seasonal or annual livestock surveys of the sort used for computing area average mortality, the index used in the developing world's other IBLI contract, in Mongolia. The ALRMP data we use in contract design are collected for the Government of Kenya, which might have a material interest in IBLI contract payouts, thereby rendering those data unsuitable as the basis for the index itself. Consistent weather data series at sufficiently high spatial resolution are likewise not available. The Kenya Meteorological Department station rainfall data for northern Kenya exhibit considerable discontinuities and inconsistent and unverifiable observations. Rainfall estimates based on satellite-based remote sensing remain controversial within climate science.[37]

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

NDVI is a satellite-derived indicator of the amount and vigor of vegetation, based on the observed level of photosynthetic activity (Tucker 2005). Images of NDVI are therefore sometimes referred to as "greenness maps." Because pastoralists routinely graze animals beyond the 8 km^2 resolution of the data, we average observations for each period within a grazing range defined as the rectangle that encompasses the residential locations and water points used by herders in each community, plus 0.02 degrees (about 10 kilometers) in each direction.[38] In unobserved bad years, pastoralists may travel further still, but their need to do so should be reflected in pasture conditions within their normal grazing range. NDVI data are commonly used to compare the current state of vegetation with previous time periods in order to detect anomalous conditions and to anticipate drought (Peters et al. 2002; Bayarjargal et al. 2006) and have now been used by many studies that apply remote sensing data to drought management (Kogan 1990, 1995; Benedetti and Rossini 1993; Hayes and Decker 1996; Rasmussen 1997).

4.4 Designing Vegetation Index Based Livestock Insurance for Northern Kenya

Recent research finds that humanitarian emergencies in this region – indicated by widespread severe child malnutrition – can be predicted reasonably accurately several months in advance. Furthermore, the recent droughts with dire consequences – in 1997, 2000 and 2005-06 – were all characterized not only by low rainfall, but also by

[38] To define location boundary for the three locations with available GPS for water points, we first identified GPS bound on each side of the rectangular among all the available GPS points and extended 0.02 degree (around 10 km.) to each side of the GPS bound. And thus, eastbound of the rectangular = max (the available GPS Y-coordinate) +0.02, westbound = min (the available GPS Y-coordinate) - 0.02, northbound of the rectangular = max (the available GPS X-coordinate) +0.02 and southbound = min (the available GPS X-coordinate) - 0.02. The result for each location is a rectangle boundary containing all the common water points, GPS of representative households in the ALRMP survey and the current household-level survey in each location.

the spatial extent and duration of the low rainfall event and its effects on rangeland conditions (Chantarat et al. 2007; Mude et al. forthcoming). The apparent predictability of these episodes motivates our approach to IBLI design based on predicted livestock mortality.

In order to confirm the appropriateness of our approach to IBLI contract design, from May-August 2008 we undertook extensive community discussions in five locations in Marsabit District, surveyed and performed field experiments with 210 households in those same locations. Chantarat et al. (2009c) and Lybbert et al. (2009) describe those studies, which confirmed (i) pastoralists' keen interest in an IBLI product, (ii) their comprehension of the basic features of the IBLI product we explain below, and (iii) significant willingness to pay for the product at commercially viable premium rates. Pastoralists in these communities worry about livestock loss, clearly associated this with pasture conditions, and readily accept the idea that greenness measures gathered from satellites ("the stars that move at night" in local dialectics) can reliably signal drought and significant livestock mortality. With demand for an IBLI product established, we proceed now with the specifics of contract design.

4.4.1 Contract Design

We design a seasonal contract covering the LRLD or SRSD season, each encompassing a rainy and dry season pair. Insurance contracts are sold (for approximately two months) just before the start of the rainy season and are assessed at the end of the dry period to determine whether indemnity payments are to be made. Contracts are specified per tropical livestock unit (TLU) at a pre-agreed value per TLU. Pastoralist clients choose the total livestock value to insure, pay the associated premium to the insurance broker and receive indemnity payments proportionate to their IBLI coverage in the event of a payout. The contract is specific at the location level, based on the predicted mortality rate as a function of the vegetation index specific to the grazing range of that location. It is also possible to design a one-year contract covering two consecutive seasonal contracts, consisting of two potential trigger payments per year (at the end of each dry season), although we focus here on the seasonal contracts. Figure 4.3 depicts the temporal structure of the IBLI contract.

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

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

$$M_{ils} = \overline{M}_{il} + \beta_i \left(M_{ls} - \overline{M}_l \right) + \varepsilon_{ils} \tag{4.2}$$

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

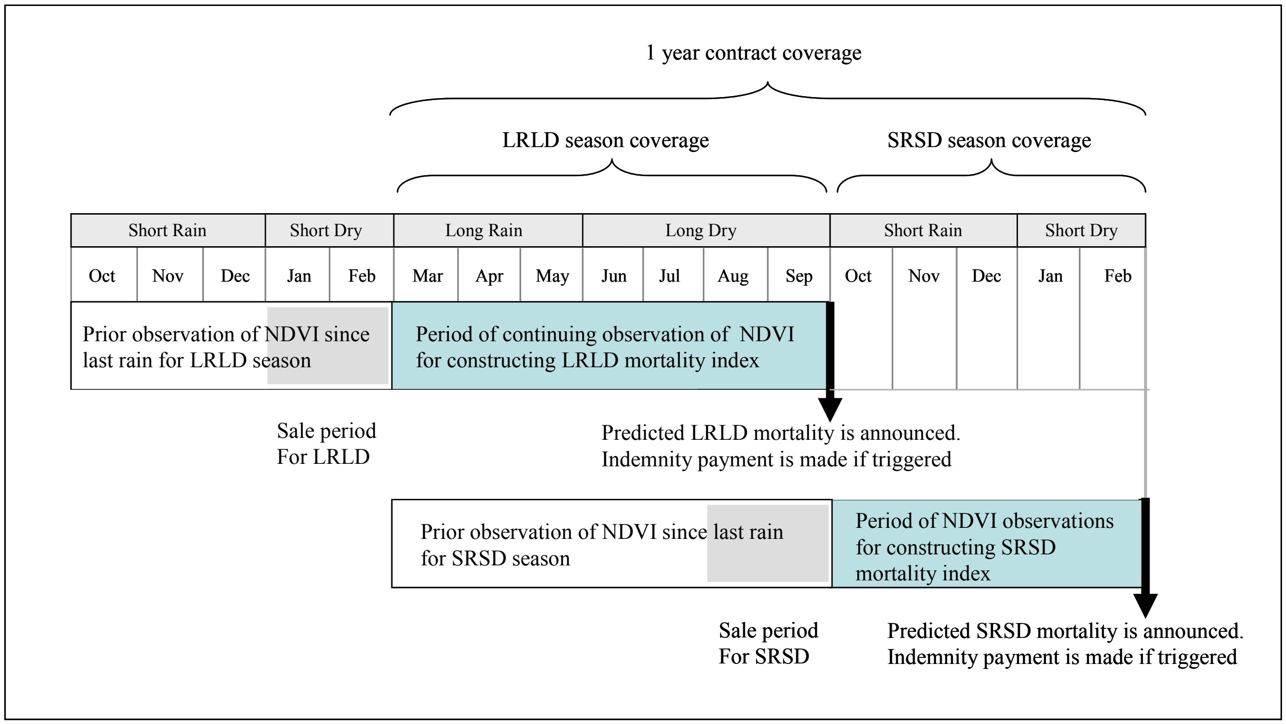

Figure 4.3 Temporal Structure of IBLI Contract

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

$$M_{ls} = M\big(X(ndvi_{ls})\big) + \varepsilon_{ls} \tag{4.3}$$

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

$$\hat{M}_{ls} = M\big(X(ndvi_{ls})\big) \tag{4.4}$$

which serves as the underlying index for insurance contract. There are thus two sources of basis risk: (i) the household's idiosyncratic losses that are uncorrelated with area average losses according to (4.2) and (ii) area average mortality losses that are not correlated with the vegetation index, according to (4.3).

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

$$\Pi_{ls}\left(\hat{M}_{ls} \mid M_l^*, TLU, P_{TLU}\right) = Max\left(\hat{M}_{ls} - M_l^*, 0\right) \times TLU \times P_{TLU} \tag{4.5}$$

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

$$P_{ls}\left(\hat{M}_{ls} \mid M_l^*, TLU, P_{TLU}\right) = E\left(Max\left(\hat{M}_{ls} - M_l^*, 0\right)\right) \times TLU \times P_{TLU} \tag{4.6}$$

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

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

$$\Pi_{lt}\left(\hat{M}_{ls\in t} \mid M_l^*, TLU, P_{TLU}\right) = \sum_{s\in t} Max\left(\hat{M}_{ls} - M_l^*, 0\right) \times TLU \times P_{TLU} \tag{4.7}$$

.

We favor the seasonal contract payout – in contrast to a yearly payout – because pastoralists' financial illiquidity typically means that catastrophic herd losses threaten human nutrition and health in the absence of prompt response. The rapid response capacity of seasonal insurance contracts is one of the great appeals of this approach to drought risk management as compared to reliance on food aid shipments, which typically involve lags of five months or more after the emergence of a disaster (Chantarat et al. 2007).

4.4.2 Variable Construction and Estimation of the Predictive Models

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

$$zndvi_{idt} = \frac{ndvi_{idt} - E_d\left(ndvi_{idt}\right)}{\sigma_d\left(ndvi_{idt}\right)} \tag{4.8}$$

where $ndvi_{idt}$ is the NDVI for pixel i for dekad d of year t, $E_d(ndvi_{idt})$ is the long-term mean of NDVI values for dekad d of pixel i taken over 1982-2008 and $\sigma_d(ndvi_{idt})$ is the long-term standard deviation of NDVI values for dekad d of pixel i taken over 1982-2008. Positive (negative) $zndvi_{idt}$ represents relatively better (worse) vegetation conditions relative to the long-term mean. Figure 4.4 depicts the NDVI and $zndvi$ series for the Marsabit locations.

We are now in the position to estimate the predictive relationship $M(\cdot)$ that maps area-average seasonal livestock mortality onto *zndvi*. But unlike crop yields that respond only to current season climate variables, livestock mortality can be the result of several seasons' cumulative effects (Chantarat et al. 2008). The lagged effects of exogenous variables raise a difficult tradeoff, however. Price stability is appealing from a product marketing perspective. Yet seasonal variation in premium rates in response to changing initial conditions, enables insurers to guard against intertemporal adverse selection problems that may arise if prospective contract purchasers understand the state-dependence of livestock mortality probabilities.

So as to minimize the tradeoff between price instability and intertemporal adverse selection, we model the predictive relationship using the shortest lag structure possible – including of only result from the preceding season – that still allows us to control for path-dependence. We estimate a regime-switching regression model with multiple regressors based on different functions of cumulative *zndv*i beginning during the paired season before the contract period begins. We now explain each of these variables in turn.

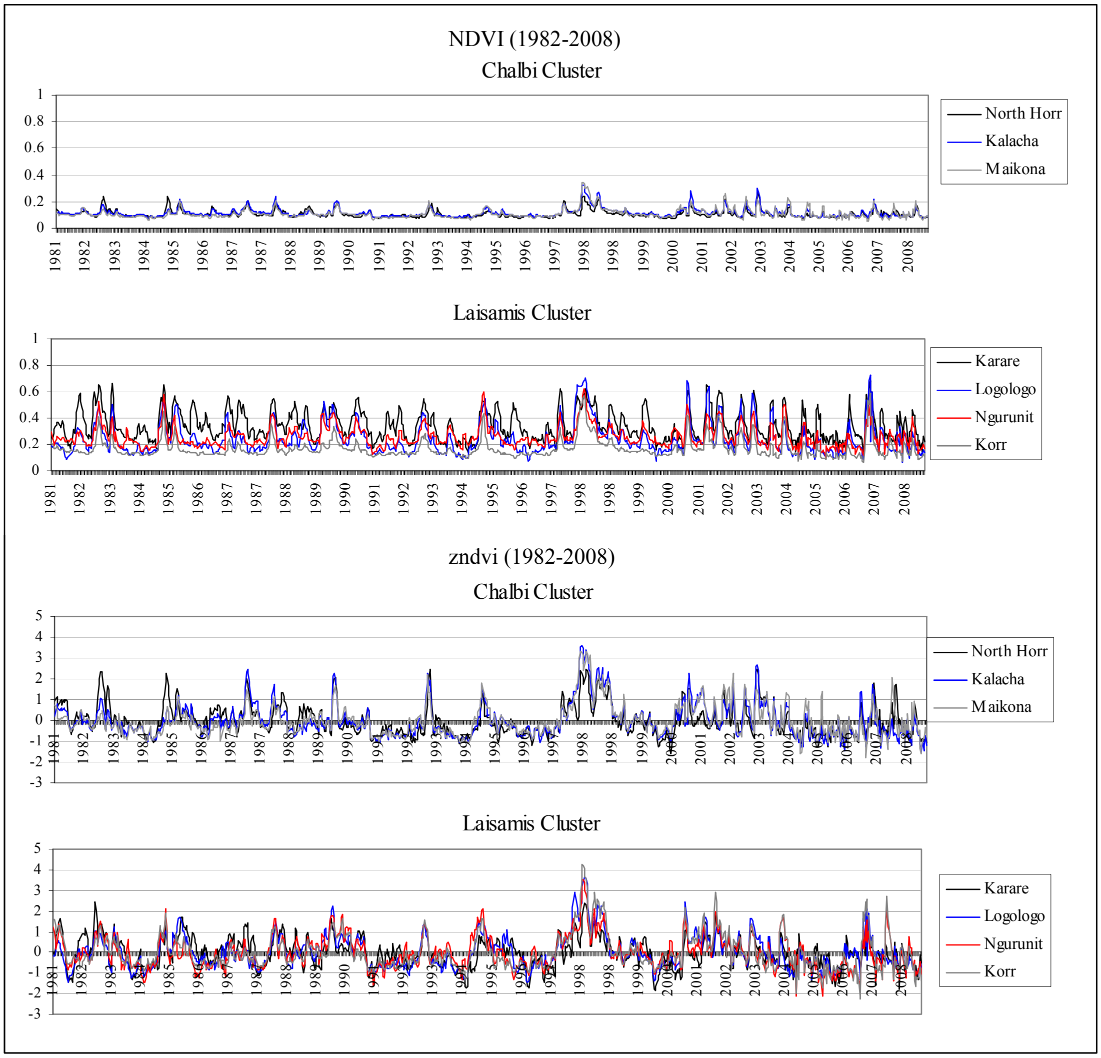

Figure 4.4 NDVI and *zndvi* for Locations in Marsabit, by Clusters

The cumulative variables we use are constructed as follows. All are depicted in Figure 4.5, which matches the seasonal IBLI contract structure with these cumulative vegetation index regressors. The first we discuss is the regime switching variable, which allows for there to exist different relationships between $zndvi_{idt}$ and area average livestock mortality depending on whether it is a good or bad season. Because we want this variable to be unobserved by all parties when the contract is struck, we use the year-long cumulative dekadal *zndvi* from the beginning of the last rainy season until the end of the contract season. Thus, for the LRLD (SRSD) contract season, $Czndvi\_pos_{st}$ runs from the first dekad of October (March), until the end of the contract period season, i.e., the last dekad of September (February):

$$Czndvi\_pos_s = \sum_{d \in T_{pos}^s} zndvi_{ds} \tag{4.9}$$

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

Thus, we estimate the relationship in (4.3) for each cluster as:

$$\begin{aligned} M_{1ls} &= M_1\left(X(ndvi_{1ls})\right) + \varepsilon_{1ls} \quad \text{if } Czndvi\_pos_{ls} \geq \gamma \quad \text{(good climate regime)} \\ M_{2ls} &= M_2\left(X(ndvi_{2ls})\right) + \varepsilon_{2ls} \quad \text{if } Czndvi\_pos_{ls} < \gamma \quad \text{(bad climate regime)} \end{aligned} \tag{4.10}$$

where $Czndvi\_pos_{ls}$ determines the climate regime into which each season belongs: a good-climate regime ($Czndvi\_pos_{ls} > 0$) or a bad one ($Czndvi\_pos_{ls} < 0$). Here, γ is the critical threshold to be determined endogenously.[39] Appendix A.1 displays descriptive statistics of the regressors and mortality data by regime.

The second cumulative vegetation index variable captures the state of the rangeland at the commencement of the contract period. This variable, $Czndvi\_pre_s$, captures cumulative *zndvi* from the start of the preceding rainy season until the start of the contract season, i.e., for LRLD (SRSD) contracts based on cumulative *zndvi* from

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

the first dekad of October (March) – the start of the preceding short (long) rains – until the first dekad of March (October), as follows:

$$Czndvi\_pre_s = \sum_{d \in T^s_{pre}} zndvi_{ds} \tag{4.11}$$

where T^s_{pre} = October – March (March – October) if s = LRLD (SRSD). Since more degraded initial conditions drive up the likelihood of livestock mortality, this variable should negatively affect predicted area average seasonal mortality. Because the insurer must set the price before prospective IBLI purchasers make their insurance decisions, the latter may have superior information, leading to some level of intertemporal adverse selection. Because most of the observations are known ex ante to both parties, however, that effect should be minimal.

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

$$CNzndvi_s = \sum_{d \in T^s} \left| Min(zndvi_{ds}, 0) \right| \tag{4.12}$$

while the positive cumulative effects analog variable is

$$CPzndvi_s = \sum_{d \in T^s} Max(zndvi_{ds}, 0) \tag{4.13}$$

where T^s = March – September (October – February) if s = LRLD (SRSD). These capture the cumulative intensity of adverse (favorable) dekads within the contract period. Catastrophic drought seasons routinely exhibit a continuous downward trend in cumulative *zndvi*, leading to a large value for *CNzndvi*, which should have a significantly positive impact on mortality. Similarly, *CPzndvi* permits us to control for post-drought recovery, when stocking rates have fallen and thus rangelands recover quickly, a phenomenon typically reflected in upward trending cumulative *zndvi*. This was the pattern observed, for example, in the SRSD seasons of 2001 and 2006 following catastrophic droughts the preceding LRLD seasons. Since these two variables capture only observations after the contract is struck, there is no information asymmetry with respect to these variables. Based on the *Czndvi* path, it thus captures not only the adverse climate impact resulted from the preceding and current rain season, but also the intensity of adverse climate.

These cumulative vegetation indices effectively capture the myriad, complex interactions between climate and stocking rates, reflected in rangeland conditions, and livestock mortality rates. We estimate simple linear regressions within each of the two regimes using the most parsimonious specification that fits the data well. With only eight years' data available for each location, limited degrees of freedom preclude estimating location-specific predictive models. Insurance companies would be unlikely to implement contracts at such high spatial resolution anyway, so this is not a serious problem. We therefore pool locations within the same cluster – treating each location's data as an iid draw from the same cluster-specific distribution – to estimate a cluster-specific predictive relationship, which we term a "response function". We also pool data for both LRLD and SRSD seasons but include a seasonal dummy to control for the potential differences across the two seasons.

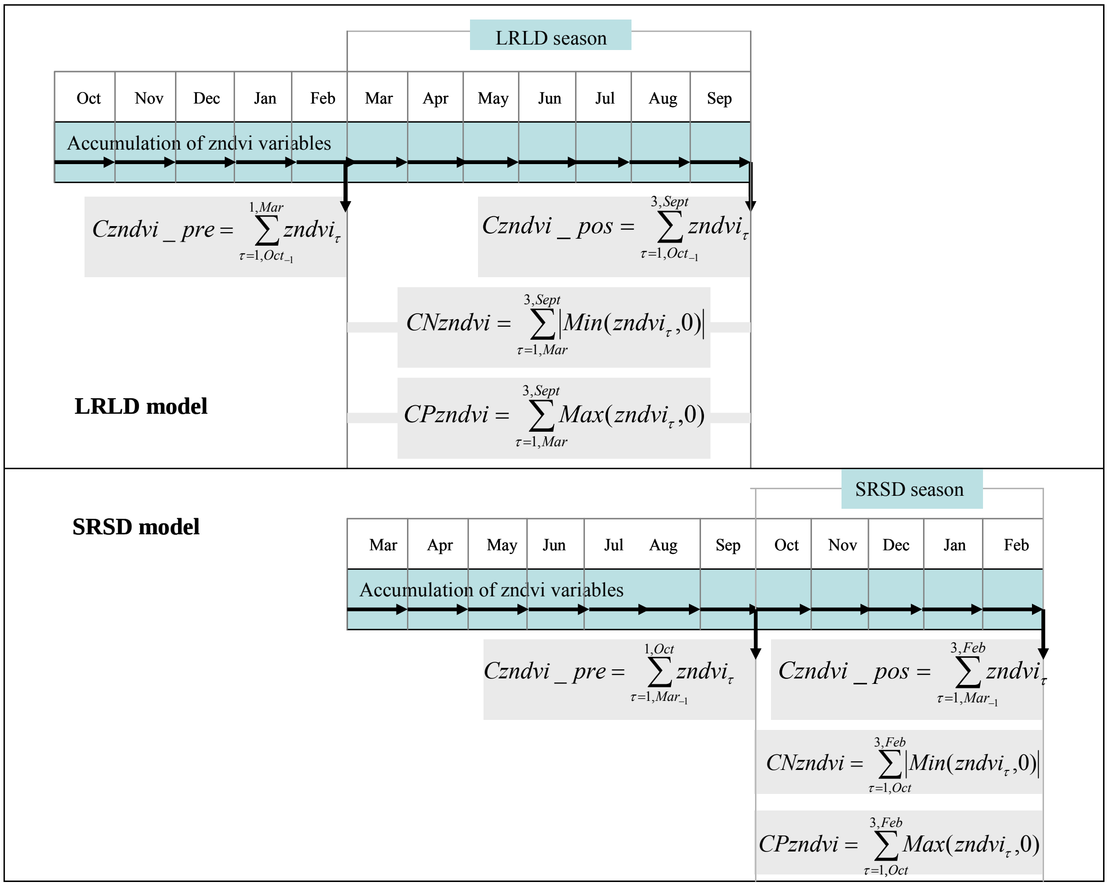

Figure 4.5 Temporal Structure of IBLI Contract and Vegetation Regressors

4.5 Estimation Results and Out-of-sample Performance Evaluation

The estimation results for equation (4.10) are reported in Table 4.3. These models explain area average mortality reasonably well, with an adjusted r^2 of 52% and 61% for Chalbi and Laisamis clusters, respectively. Livestock mortality patterns in the good climate regime are very difficult to explain, with no statistically significant relationship between any regressor and livestock mortality. Of course, this makes intuitive sense as variation in good range conditions should not have a systematic effect on livestock survival.

In the bad climate regime, however, we see precisely the patterns anticipated. The initial state of the system, as reflected in $Czndvi\_pre$, has a very strong, statistically significant negative effect on mortality rates; the "less bad" the recent rangeland conditions when the insurance contract period falls into the bad climate regime, the lower is observed herd mortality. Similarly, the greater the intensity of positive (negative) spells during the season, as reflected in $CPzndvi$ ($CNzndvi$), the lower (higher) herd mortality rates, although those coefficient estimates are statistically significant only in Laisamis cluster, where pastoralists are less migratory and thus brief spells of favorable conditions are less likely to attract transhumant herd movements to take advantage of transiently available forage and water.

Table 4.3 Regime Switching Model Estimates of Area Average Livestock Mortality

Chalbi Model			Laisamis Model		
Number of observations		48	Number of observations		64
R-squared		0.5689	R-squared		0.6554
Adj R-squared		0.5187	Adj R-squared		0.6062
Good-climate regime (Czndvi_pos>=0)			Good-climate regime (Czndvi_pos>=0)		
Mortality	Coeff.	Std.Err	Mortality	Coeff.	Std.Err
Czndvi_pos	0.0024	0.0018	Czndvi_pre	-0.0003	0.0028
			CNzndvi	0.0087	0.0081
			CPzndvi	0.0013	0.0024
			SRSD	0.0147	0.0402
Bad-climate regime (Czndvi_pos<0)			Bad-climate regime (Czndvi_pos<0)		
Mortality	Coeff.	Std.Err	Mortality	Coeff.	Std.Err
Czndvi_pre	-0.0187***	0.0051	Czndvi_pre	-0.0093***	0.0024
CNzndvi	0.0018	0.0033	CNzndvi	0.0117***	0.0022
CPzndvi	-0.0064	0.0087	CPzndvi	-0.0111**	0.0049
SRSD	0.0354	0.0564	SRSD	-0.0446*	0.0299

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

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

The limited size of the ALRMP sample precludes setting aside some of those data for out of sample performance evaluation. But we can use the PARIMA survey data, which cover four seasons (2000-2002) in four locations (Kargi and North Horr in Chalbi cluster, and Logologo and Dirib Gumbo in Laisamis cluster) in the same region, but were not used to estimate the predictive model,[40] to test out of sample forecast accuracy. Predicted area average mortality rates for these locations were then constructed based on the established cluster-specific response functions and location-specific NDVI data.

Define forecast error as the difference between actual area average mortality rate less the predicted mortality rate. A positive forecast error thus implies underprediction of the mortality rate, which would favor insurers; a negative error indicates overprediction of mortality, which could benefit insurance holders. Table 4.4 reports the distributions of out of sample forecast errors by cluster. In each case, 7/8 (88%) of errors were less than 10% in absolute magnitude, with one single observation

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

off by more than 25%, an under-(over-)prediction in Dirib Gumbo (North Horr) in the 2000 SRSD season.

Table 4.4 Out of Sample Forecast Performance

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

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

We also tested the performance of the IBLI contract in correctly triggering decision for insurance payouts at different strike levels. The errors of greatest concern are when the insured are paid when they should not be (type 1 error) or not paid when they should have been (type 2 error). Table 4.5 reports those results. The minimum frequency of correct decisions out of sample is 75%, with 94% overall accuracy (averaging Chalbi and Laisamis clusters) at a strike level of 15% mortality on the IBLI contract.

Table 4.5 Testing Indemnity Payment Errors

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

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

As another diagnostic over a longer period, we compare well-known severe drought events reported by communities with the predicted area average mortality constructed using their available dekadal NDVI data from 1982-2008. We find the predicted mortality index time series quite accurately capture the regional drought events of 1984, 1991-92, 1994, 1996, 2000 and 2005-06, predicting average herd mortality rates of 20-40% during those seasons and never generating predictions beyond 10% in seasons when communities indicate no severe drought occurred.[41] This is a more statistically casual approach to forecast evaluation, but encompasses a longer time period and we find it effective for communicating to local stakeholders the potential to use statistical models to accurately capture average livestock mortality experience for the purposes of writing IBLI contracts.

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

4.6 Pricing and Risk Exposure Analysis

The predicted mortality profiles just describe are a key input for determining the distribution of predicted area average herd mortality rates – a vegetation-based livestock index for IBLI – and thus the actuarially fair price of IBLI based on historical data. Summary statistics of the main locations are shown in Table 4.6. On average, predicted mortality is lower in Laisamis than in Chalbi, with higher predicted mortality and larger variability during the SRSD (LRLD) season in Chalbi (Laisamis) cluster and higher probability of indemnity payout for any strike level in Chalbi than in Laisamis.

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

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

Table 4.6 Predicted Seasonal Mortality Rates, 1982-2008

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

4.6.1 Unconditional Pricing

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

$$p_{ls}\left(\hat{M}_{ls} \mid M_l^*\right) = \frac{1}{S}\sum_{s=1}^{S} Max\left(\hat{M}_{ls}(zndvi_{ls}) - M_l^*, 0\right) \qquad (4.14)$$

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

Table 4.7 reports the fair insurance premium rates (%), their standard deviations and US dollar equivalent premia per TLU insured[42] for seasonal contracts with various strikes for locations. Because episodes of high die-offs are more frequent in Chalbi than in Laisamis (Table 4.6), fair premium rates are likewise higher there. But the rates are reasonable, only 2-5% of the insured livestock value for the coverage beyond 10% mortality per season and 1-2% of the insured livestock value for coverage beyond 20% mortality per season.

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

Table 4.7 Unconditional Fair Seasonal Premium Rates at Various Strike Levels

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

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

$$p_{lt}\left(\hat{M}_{ls} \mid M_l^*\right) = \frac{1}{T}\sum_{t=1}^{T}\sum_{s \in t} Max\left(\hat{M}_{ls}(zndvi_{ls}) - M_l^*, 0\right) \tag{4.15}$$

where T covers the available 27 years of data. The fair premium rates (%), standard deviations and US dollar equivalent premia per TLU are reported in the top panel of Table 4.8. Intuitively, the annual premium is roughly twice as much as the seasonal premium. Fair annual premium rates decline as the strike mortality increases, e.g., from 5-9% at a strike of 15%, to 3-5% for strike mortality of 20%, to just 1-3% at a strike of 20%. By having pastoralists retain the layer of small risks, index insurance appears affordable even in the face of recurring severe droughts. Depending on the pastoralist's location and chosen strike rate, a herder needs to sell one goat or sheep to pay for annual insurance on 1-10 camels or cattle, an expense they appear willing to incur (Chantarat et al. 2009b and 2009c).

4.6.2 Conditional Pricing

Because expected mortality depends on the state of the system, the probability of catastrophic herd loss increases with rangeland vegetation conditions observable prior to the contract purchase. In order to guard against intertemporal adverse selection, insurers might adjust insurance premia accordingly. The simplest way is to price the contract conditional on the observed cumulative $zndvi$ from the beginning of the last rainy season until the beginning of the sale period, $Czndvi\_beg_{ls}$, covering the preceding October-December (March – July) for LRLD (SRSD) contracts, assuming a two month sales period in January-February (August-September).

Table 4.8 Unconditional Vs. Conditional Fair Annual Premium Rates

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

Using the regime threshold $Czndvi\_beg_{ls} = 0$ analogous to that found in our earlier estimation, the two conditional annual premia based are simply:

$$p_{lt}\left(\hat{M}_{ls} \mid M_l^*, Czndvi\_beg_{ls} \geq 0\right) = E\left(\sum_{s \in t} Max(\hat{M}_{ls} - M_l^*, 0) \mid Czndvi\_beg_{ls} \geq 0\right) \tag{4.16}$$

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

As Table 4.8 shows, the two conditional premia vary markedly. When the ex ante rangeland state is favorable, premia are only 2-5% for contracts with a 10% strike. But when the state of nature is bad, those rates jump to 9-11%. Given marketing and political considerations, it is unclear whether insurers will be willing to vary IBLI premia in response to changing ex ante range conditions, leaving open a real possibility of intertemporal adverse selection issues.

4.6.3 Risk Exposure of the Underwriter

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

We estimate underwriter risk exposure under the following assumptions. First, we assume equal insurance participation covering 500 TLU in each of ten locations[43] in Marsabit district for a total liability of $75,000/location. A standard insurance loss ratio (L_t) for a portfolio in year t that consists of L locations' coverage is

$$L_t = \frac{\sum_{l \in L} \Pi_{lt}}{\sum_{l \in L} \mathrm{P}_{lt}} \tag{4.17}$$

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

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

Table 4.9 reports the probability distribution of the yearly loss ratios associated with underwriting contracts with different strikes and (conditional or unconditional) pricing for the full set of ten locations. The loss ratio over a τ - year time period of the insurance portfolio that covers L locations is calculated as[44]

---

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

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

$$L_{\tau} = \frac{\sum_{t\in\tau}\sum_{l\in L}\Pi_{lt}}{\sum_{t\in\tau}\sum_{l\in L}\mathrm{P}_{lt}} \tag{4.18}$$

As Table 4.9 indicates, for the most exposed case of 10% strike contracts with unconditional premium pricing, the single year risk of a loss ratio greater than 2 is 26%, but this falls to just 8% with two year pooling and to zero when risk is pooled over a five-year period. Of course, the reduced loss exposure risk necessarily comes at the cost of lower probability of large profits from the contract. Figure 4.6 presents a sample cumulative distribution of the loss ratios reported in Table 4.9, clearly showing how a state-conditional pricing – which allows insurers to collect more premium in the seasons with high probability of indemnity payout – and longer-term commitment – which allows insurers to average out extreme losses and gains over time – each reduce extreme outcomes sharply.[45] Of course, with premium loadings, underwriter risk exposure would further be reduced further relative to these estimates based on pure premia.

[45] Due to asymmetry in the distributions of loss ratio – skewness associated with low probability of extremely high loss ratio – the cumulative distribution functions in each panel of Figure 4.6, therefore, do not all intersect at 1 at 50% cumulative probability.

Table 4.9 Distribution of Estimated Loss Ratios

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

Note: The shaded zone represents the scenario when underwriter experiences loss (loss ratio greater than 1).

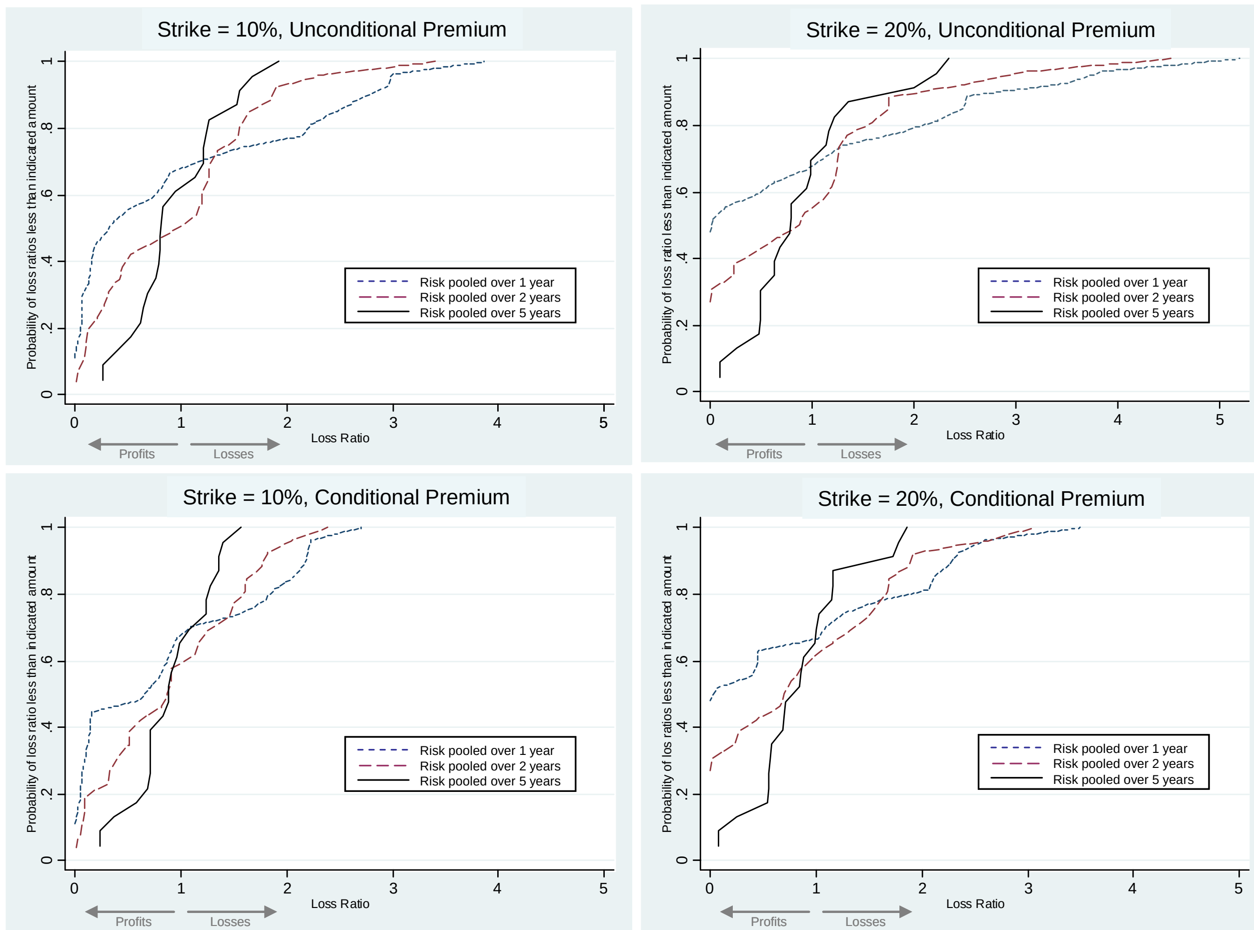

Figure 4.6 Loss Ratio Cumulative Distributions, by Pricing, Strike and Number of Years Risk Pooled

We now consider a simple reinsurance strategy where the loss beyond 100% of the pure premium is transferred to a reinsurer. For contracts with unconditional (conditional) premia, actuarially fair stoploss reinsurance rates quoted as percentage of IBLI premium would range from 49% (32%) for a 10% strike contract to 68% (49%) for a 30% strike contract (Table 4.10). Appendix A.3 shows the detail. These high estimated pure reinsurance rates only take into consideration the local drought risk profile, however, and should fall markedly as international reinsurers are better able to diversify these risks in international financial markets. Indeed, this diversification opportunity through international risk transfer is one of the key benefits of developing IBLI products.

Table 4.10 Mean Reinsurance Rates for 100% Stop Loss Coverage

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

4.7 Conclusions and Some Implementation Challenges

This paper has laid out why index based livestock insurance (IBLI) is attractive as a means to fill an important void in the risk management instruments available to pastoralists in the arid and semi-arid lands of east Africa, where insurance markets are effectively absent and uninsured risk exposure is a main cause of the existence of poverty traps. It has gone on to explain the design of an IBLI product to insure against livestock mortality in order to protect the main asset households in this region hold. We parameterize the index using longitudinal observations of household-level herd mortality, fit to high quality, objectively verifiable remotely sensed vegetation data not manipulable by either party to the contract and available at low cost and in near-real time. The resulting index performs very well out of sample, both when tested against other household-level herd mortality data from the same region and period and when compared qualitatively with community level drought experiences over the past 27 years. Finally, we established that IBLI should be readily reinsurable on international markets.

The development of the IBLI contract is promising because of the opportunity it opens up to bring insurance to many places where uninsured risk remains a main driver of poverty. Extended time series of remotely sensed data are available worldwide at high quality and low cost. Wherever there also exist longitudinal household-level data on an insurable interest (livestock, health status, crop yields, etc.), similar types of index insurance can be designed using the basic techniques outlined here.

A range of implementation challenges nonetheless remain and are the subject of future research. First, the existence of household-level data permit direct exploration of basis risk, looking in particular for any systematic patterns so that prospective insurance purchasers can be fully informed as to how well suited (or not) the index-based contract might be for their individual case. Chantarat et al. (2009b) explores this issue for this IBLI product.

Second, and relatedly, experience with other index-insurance pilots has shown that a carefully designed program of extension to appropriately educate potential clients is necessary for both initial uptake and continued engagement with insurance

(Gine et al., 2007; Sarris et al., 2006). Complex index insurance products can be difficult to understand, especially for populations with low levels of literacy and minimal previous experience with formal insurance products. Preliminary experiments with using simulation games in the field with prospective insurance purchasers shows significant promise as a means of both explaining how index insurance products work and generating demand for the product (Lybbert et al. 2009).

Third, the infrastructure deficiencies that lead to high transactions costs in verifying individual claims in remote rural areas still feed high costs of product marketing and claims settlement. Development of cost-effective agent networks for reliable, low-cost product marketing and service is a challenge. In the northern Kenya IBLI case, our commercial partners are tapping into a network of local agents equipped with electronic, rechargeable point-of-sale (POS) devices being extended throughout northern Kenya by a commercial bank working with the central government and donors on a new cash transfer program. These POS devices can be easily configured to accept premium payments and to register indemnity payments for certain insurance contracts. Financial sector interests are attracted by the potential economies of scope involved in introducing another range of products for devices otherwise used purely for government payments and debit payments.

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

These implementation challenges notwithstanding, IBLI shows considerable promise as effective drought risk management strategies and widely acknowledged as essential components to effective poverty alleviation in the pastoral areas of east Africa. By addressing serious problems of covariate risk, asymmetric information and high transactions costs that have precluded the emergence of commercial insurance in these areas to date, IBLI offers a novel opportunity to use financial risk transfer mechanisms to address a key driver of persistent poverty. Hence the widespread interest shown in IBLI by government, donors and the commercial financial sector. The design detailed in this paper overcomes the significant challenges of a lack of reliable ground climate data (e.g., from location rainfall station) or seasonal or annual livestock census data, as well as the need to control for the path dependence of the effects of rangeland vegetation on livestock mortality. As the product goes into the field in the coming months, the true test of IBLI viability and impact will come from monitoring households in the test pilot areas and the financial performance of the institutions involved in offering these new index-based livestock insurance contracts.

CHAPTER 5

BASIS RISK, EX ANTE WEALTH AND THE PERFORMANCE OF INDEX BASED LIVESTOCK INSURANCE IN THE PRESENCE OF A POVERTY TRAP

5.1 Introduction

In the past 100 years, northern Kenya recorded 28 major droughts, four of which occurred in the last ten years (Adow 2008). Among more than three million pastoralist majorities, whose livelihoods rely partially or solely on livestock, severe droughts always come with widespread livestock mortality that places a considerable strain on pastoralists' livelihoods and welfare dynamics. With a dearth of alternative productive livelihood strategies to pursue in Kenya's arid and semi-arid areas and failures in the formal insurance market and scant risk-management options to provide adequate safety nets in the event of shock, the link between exposures to covariate risk, vulnerability and poverty becomes significantly stronger in these areas.

The potential of index-based livestock insurance (IBLI) for managing livestock mortality risk in northern Kenya as a complement to broader and more comprehensive risk-management and social protection programs pursued by the Government and international organizations has been extensively identified in Chantarat et al. (2009a). Like typical insurance, IBLI compensates for livestock loss. But unlike traditional insurance, it only compensates for the covariate herd losses that are objectively and transparently observable. In the case of northern Kenya, the increasingly popular remotely sensed Normalized Differential Vegetation Index (NDVI), an indicator of vegetative cover widely used in drought monitoring programs in Africa, is used to predict covariate herd mortality in a particular location. An objectively measured predicted herd mortality index constructed from such strong predictive relationship is then used to trigger IBLI's indemnity payments for the insured in such coverage area.

By design, IBLI thus has significant advantages over traditional insurance. Since the payment is no longer based on individual claims, insurance companies, as well as insured clients, only have to monitor the index to know when a claim is due and indemnity payments must be made. The transaction costs of monitoring and verification are considerably reduced. This is especially important in remote, infrastructure-deficient areas like northern Kenya where transaction costs have often been the limiting factor for traditional insurance markets. And since the index is objectively measured and can not be influenced by insurer or insuree, it avoids the twin asymmetric information problems of adverse selection and moral hazard that have long plagued conventional insurance products. IBLI thus offers great promise as a marketable risk management instruments in this targeted region.

The gains in reduction of transaction costs and incentive problems, however, come at the cost of "basis risk", which refers to the imperfect correlation between an insured's potential livestock loss experience and the behavior of the underlying index on which the index insurance payout is based. It is possible that a contract holder may experience livestock losses but fail to receive a payout if the overall index is not triggered. Similarly, while the aggregate experience may result in a triggered contract, there could be individuals who experience minimal losses but still receive payouts. This tradeoff between basis risk and reductions in incentive problems and insurance costs is thus a critical determinant of the risk management effectiveness of IBLI.

On the basis of a successfully designed IBLI contract (Chantarat et al. 2009a), this paper uses household level analysis to examine the effectiveness of IBLI contracts in managing asset risk and improving the welfare dynamics of the target community.

Our objective is to use two complementary household-level panel data sets[46] to simulate representative households based on observed distributions of various relevant characteristics, and use these to analyze the performance of various IBLI contracts based on a stylized dynamic model that replicates the herd wealth dynamics of pastoralists in northern Kenya. This technique will also allow us to study patterns of potential demand for the particular product and to derive some implications for using IBLI as part of poverty alleviation program in the region. Given the innovative nature of the IBLI contract, the production dynamics of northern Kenya and the rich data sources we employ, our analysis adds to the current literatures in many interesting ways.

First, we emphasize the value of IBLI in managing asset risk, which is distinguishable from transitory income risk, widely analyzed in the current literatures that evaluate the potential of agricultural insurance in reducing farm income losses. Unlike income shocks, shocks on productive assets like livestock perturb the entire asset accumulation process, and so will potentially create intertemporal impacts on the future income and livelihoods relying on affected assets. The intertemporal impact of asset shocks is even stronger in an economic setting characterized by a bifurcation in asset accumulation dynamics evidenced in northern Kenya pastoral production, leading to the existence of poverty traps. Lybbert et al. (2004), Barrett et al. (2006), Santos and Barrett (2007), among others, have found evidence in the region of a critical herd accumulation threshold, below which the herds collapse into a

[46] None of the two data sets was used in the design of IBLI. The more temporally rich repeated monthly livestock mortality data from 2000-2008 household survey collected by the Government of Kenya's Arid Land Resource Management Project (ALRMP) was used in the designing process in Chantarat et al. (2009a). That data set, however, is not a panel data set and so they can, at best, provide inference on the location-level mortality dynamics.

decumulation trajectory toward some low-level poverty trap and above which it catches a growth trajectory toward a high level equilibrium.

Where production dynamics are characterized by critical herd thresholds, shocks that push herd sizes below the threshold can irreversibly impact the herd accumulation process. Consequently, insurance that can protect households from slipping into the poverty trap can be of significant value. Aware of this bifurcation threshold, pastoralist's valuation of insurance will also involve intertemporal expectation of asset accumulation dynamics. We thus evaluate IBLI's performance using a dynamic model rather than the static one employed in the current literature. We elaborate that effectiveness of IBLI and so household's insurance valuation will also depend on their herd level relative to the realized bifurcation threshold, in addition to their basis-risk-determining characteristics and risk preference.

Second, whereas the norm in the literature[47] assumes a representative individual generated from community-level data, we evaluate IBLI performance based on observed household-level variations in characteristics such as individual-specific degrees of risk exposure, inherent basis-risk indicating characteristics, herd size and risk attitude. The contracts that perform well with a representative (area-averaged) household may not prove to be effective for the majority of the area if distributions of these key individual-specific characteristics are highly dispersed. Household-level analysis allows us to study patterns of such variations.

Third, where much of the literature relies on risk preference assumptions, our analysis is based on observed risk preference estimates elicited using field experiments. Based on the distribution of observed risk preference, certainty equivalent herd growth rates are constructed to reflect certain growth rates that yield similar intertemporal utility as that obtained from household's stochastic growth.

[47] See for example, Skees et al. 2001; Turvey and Nayak 2003; Vedenov and Barnett 2004; Deng 2007.

Improvement in the certainty equivalent growth rate of the insured herd relative to the no-insurance case thus serves as our evaluation criterion for IBLI. This technique also enables us to explore variation of households' willingness to pay and aggregate demand for the IBLI product, which provide critical insight regarding commercially targeting and identification of those likely to rely on the government or NGO for subsidization as part of the social program.

And so lastly, though our primary objective is to catalyze a commercially sustainable market to deliver the product, the genesis of our intent to design IBLI was our desire to manage the risks faced by vulnerable pastoral and agro-pastoral populations and provide them with a safety net that can be implemented as a government or donor-driven social protection program in the form of subsidizing IBLI premium. Household-level analysis allows us to compare dynamic poverty outcomes of various subsidization programs and targeting schemes. Our analysis shows that targeting IBLI subsidies toward vulnerable non-poor pastoralists offers a considerable productive safety net by helping protect many such households from slipping into a poverty trap stage after catastrophic drought hits. This supports assertions that interventions targeting the non-poor can, in such systems, be poverty reducing in the long run as they reduce the ranks of vulnerable individuals from falling into poverty in the event of a shock (Barrett et al. 2008).

The rest of the paper is organized as followings. Section 5.2 provides an overview of livestock economy of the study locations and describes the data we used. Section 5.3 briefly introduces IBLI. As a basis for simulations, Section 5.4 describes a dynamic model we used in characterizing the economic settings of poverty traps and asset risk in northern Kenya. It then discusses certainty equivalent herd growth rate used as a key evaluation criterion of IBLI performance, and elaborates the potential impacts of IBLI on pastoralist's livestock asset accumulation and its performance distinguishing the significance of household's various sources of basis risks and other key characteristics. Section 5.5 estimates distributions of basis-risk-determining parameters, risk preference and other key household characteristics necessary for the simulations. Using the estimated distributions and 54 seasons from 1982-2008 of available vegetation index, we then discuss our simulation strategies and baseline results of the simulations. Section 5.6 presents the resulting IBLI performance and its variations from the overall simulation results. Based on these results, Section 5.7 then estimate households' willingness to pay for the optimal contract in each location, constructs district-level aggregate demand for IBLI and studies its patterns and variations across wealth groups. Section 5.8 then discusses varying dynamic outcomes of various targeted subsidizing IBLI. And finally, Section 5.9 concludes.

5.2 Overview of Pastoral Economy in the Study Areas and Data

Northern Kenya's climate is generally characterized by bimodal rainfall that disaggregates the agricultural calendar in this region into two seasons, each with a pair of rainy and dry periods. A year starts with long rain (falling March-May)-long dry (June-September) season, which we henceforth refer to as LRLD, and follows by short rain (falling October-December)-short dry (January-February) season, hereafter referred to as SRSD. Pastoralists rely on both rains for water and pasture for their animals. Pastoralism in the arid and semi-arid areas of northern Kenya is nomadic in nature, where herders commonly adapt to spatiotemporal variability in forage and water availability through herd migration.

Livestock represent the key source of livelihood across most households in this environment, but face considerable mortality risk largely related to drought, rendering pastoral households vulnerable to herd mortality shocks. As part of the IBLI pilot project in Marsabit District in northern Kenya, this study investigates the performance of IBLI in four locations in the district: Dirib Gombo, Logologo, Kargi and North Horr. These four study locations marked in Figure 5.1

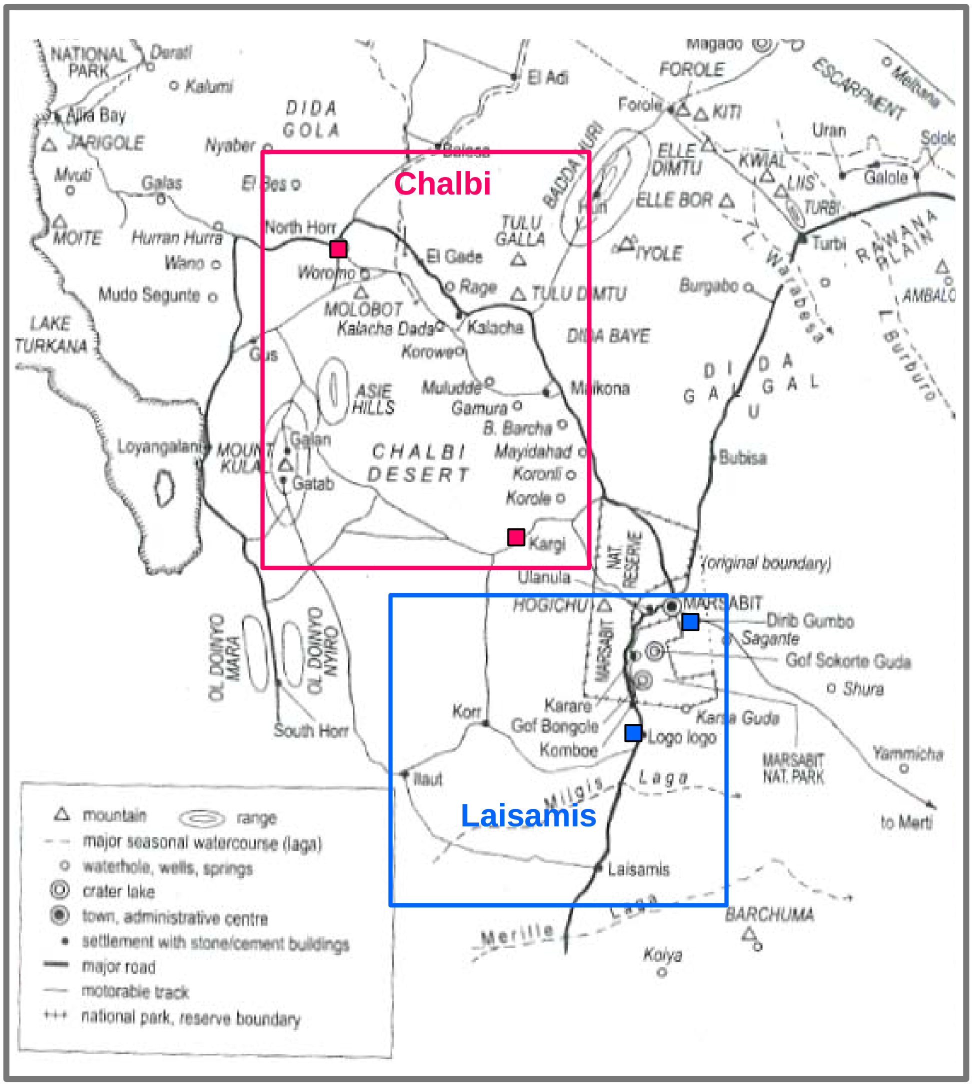

Figure 5.1 Study Areas in Northern Kenya

These four locations are the overlapping survey locations of the two complementary household-level data sets. First is the household-level panel data collected quarterly by the USAID Global Livestock Collaborative Research Support Program (GL-CRSP) "Improving Pastoral Risk Management on East African Rangelands" (PARIMA) in these locations from 2000-2002 (Barrett et al. 2008). Thirty households were randomly selected in each of the survey location and the household heads were interviewed. In each location, a baseline survey was conducted in March 2000. Repeated surveys were conducted quarterly for an additional nine periods through June 2002. Data on household's seasonal livestock losses, mortality, growth and offtake were then reconstructed to match the agricultural calendar by combining two quarters into the season system. And so these main variables are available for four seasons: LRLD 2000, SRSD 2000, LRLD 2001 and SRSD 2001, which also cover a major drought that affected much of the areas in 2000.

We complement the current set with the household surveys fielded specifically in these locations during May-August 2008. The main objectives of this survey were to gain insights of pastoralists risk experience, their historical herd dynamics, their risk appetite, their perceptions of climactic variability and also to gather household level information that is likely to be correlated to these variables.[48] The sample was stratified by wealth class: low, medium and high, based on owned herd size classified by community standards.[49] For the sample size of 42 households in each location, approximately 14 households were randomly drawn from these location-wealth strata. The survey was conducted in June-July 2008, though many key questions gathered

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[48] In addition we aimed to introduce potential clients to the concept of IBLI, and to investigate patterns and determinants of willingness to pay for IBLI. Chantarat et al. 2009c describes this data set in more detail).

[49] Wealth classification standards vary by location. The boundaries in TLU for (L,M,H) wealth class for the five locations are Dirib(<3,3-8,>8), Kargi(<15, 15-25,>25), Karare(<15,15-30,>30), Logologo(<10,10-25,>25) and North Horr(<15,15-35,>35).

recalled information over the season for the preceding year. This allows us to construct the main variables on seasonal mortality, growth and offtake for two seasons: LRLD 2007 and SRSD 2007. This data set also includes pastoralist's risk perception estimates elicited from a simple 50-50 lottery game with real monetary payoff described in Section 5.5.

Table 5.1 summarizes the key characteristics[50] of the pastoral economy in the four study locations representing diversity in ethnicity, pastoral production system, climate and geographical resources. They range from the least arid location of Dirib Gombo occupied mostly by cattle- and smallstock-based pastoralists, who also rely on town-based livelihood opportunities to complement there meager livestock resource; to Logologo with relatively more arid climate and relatively larger number of large-scaled, cattle- and smallstock-based and migratory pastoralism; to the very arid locations at the opposite edge of the Chalbi dessert, Kargi and North Horr, with many large-scaled, camel- and smallstock-based pastoralists with extensive migratory patterns due to harsher spatiotemporal variability in forage and water availability.

Mean herd sizes range from the lowest of 2 TLU per household in Dirib Gombo to the highest of 25 TLU in North Horr. Livestock is considered the main component of pastoralist's asset. Livestock also represents the key source of livelihood with households relying on livestock and livestock products for 44-87% of their income. The location with the lowest mean herd size, Dirib Gombo, exhibits the highest income poverty (with respect to \$0.5/day poverty line) as well as asset poverty (with respect to 10 TLU livestock unit), while these poverty incidences are the lowest in the location with the highest mean herd size, North Horr. This evidence thus further emphasizes the significance of livestock as a component of livelihoods among pastoralists and agro-pastoralists in northern Kenya.

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[50] Note that all summary statistics are weighted by appropriate stratified sampling weights.

Livestock mortality is considered the main threat to the livelihood of pastoralists in this environment. Households' overall seasonal livestock loss experiences during 2000-2002 (covering bad drought in 2000) varied within and across locations range from the lowest averaged seasonal rate of 7% in North Horr to 21% in Dirib Gombo. Extreme herd losses occurred in high frequency in these regions with greater-than-20% seasonal losses occurred with probability of around 20% (10-15%) in Dirib Gombo and Logologo (in Kargi and North Horr). Strikingly, there were at least 10% probabilities of greater-than-50% seasonal losses in Dirib Gombo.

Table 5.1 Descriptive Statistics of Supportive Variables, 2007-2008

Variables/Location	Dirib Gombo		Logologo		Kargi		North Horr	
Climate	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Annual Rainfall (mm)	366	173	297	137	270	115	227	86
NDVI	0.30	0.11	0.24	0.12	0.15	0.05	0.11	0.03
Livestock Composition	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
% Camel	0%	4%	3%	9%	10%	5%	9%	8%
% Cattle	28%	34%	26%	18%	2%	3%	2%	3%
% Small stock	72%	34%	71%	19%	88%	6%	89%	9%
% Migration	6%	21%	87%	21%	88%	16%	88%	17%
Asset (per household)	Median	S.D.	Median	S.D.	Median	S.D.	Median	S.D.
Livestock (TLU)	2	4	16	22	17	10	25	19
Nonlivestock (1,000 Ksh)	31	53	0	3,553	0	46	10	60
Income (per capita)	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Annual income (1,000 KSh)	3	6	12	11	6	10	27	58
% Livestock share	29%	39%	70%	40%	90%	27%	77%	39%
% Salary/business	41%	43%	26%	40%	5%	21%	20%	39%
Seasonal livestock loss (%)	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
In 2000-02 (drought in 2000)	21%	29%	15%	19%	11%	12%	7%	10%
Poverty Incedence								
% Headcount (0.5$/day)	98%		73%		91%		63%	
% Headcount (10 TLU)	97%		52%		30%		18%	

Note: % Migration represents percentage of herd that moves at least once over the year. An average value of 1 TLU is approximately 12,000 Ksh, an equivalent of $150 based on November 2008 exchange rates (79.2Ksh/US$).

Investigating the composition of historical herd loss from 2000-02 and 2007-08 in the observed data sets also implies that catastrophic herd losses tend to result from covariate shocks over the rangeland – e.g., water and forage availability – in contrast to the small-scaled herd losses, which tend to result from other seemingly idiosyncratic shocks, e.g., accident or conflict. This evidence thus naturally provides logic behind the design and development of vegetation index based insurance to provide cost-effective coverage for a specific (but major) component of livestock asset risk in this region.

5.3 Index Based Livestock Insurance

From the set of vegetation index $(ndvi_{lt})$ observed prior to and throughout the season t in each location l, Chantarat et al. (2009a) constructed predicted herd mortality index based on well-established seasonal forecasting relationships according to $\hat{M}_{lt} = \hat{M}(ndvi_{lt})$. The constructed index thus serves as the underlying index triggering indemnity from IBLI for that particular location relative to a pre-specified level, know as the "strike".

An IBLI contract $\left(M^*, \hat{M}(ndvi_{lt})\right)$ with coverage season t and the spatial coverage l make indemnity payment rate (as percentage of the insured herd value) conditional on the realization of $\hat{M}(ndvi_{lt})$ and the strike M^* according to:

$$\pi_{lt}\left(M^*, \hat{M}(ndvi_{lt})\right) = Max\left(\hat{M}(ndvi_{lt}) - M^*, 0\right) \tag{5.1}$$

For IBLI to sustain commercially, a premium loading $a \geq 0$ over the actuarial fair rate – estimated based on the empirical distribution of NDVI – will be applied to take into account costs of administrative and un-known exposures.[51] And so the loaded

[51] The average premium loading for agricultural insurance contract is in the range of 30-50% (see for example the USDA Risk Management Agency (RMA)'s or the Farmdoc's Premium Estimator for

premium rate for coverage season t and location l quoted as a percentage of total value of insured herd, can be calculated as

$$\rho_{lt}^{a}\left(M^*, \hat{M}(ndvi_{lt})\right) = (1+a)E\pi_{lt} = (1+a)\int Max\left(\hat{M}(ndvi_{lt}) - M^*, 0\right)df(ndvi_{lt}) \qquad (5.2)$$

Table 5.2 provides summary statistics of these predicted mortality index $\hat{M}(ndvi_{lt})$ for each of the four study locations constructed using the full NDVI series available in real time from 1982-2008. The predicted herd mortality indices are averaged at 8-9%. Though North Horr was shown earlier to have the least mean and standard deviation of the overall household's livestock losses during 2000-2002, it exhibits the highest magnitude and variation of the predicted seasonal herd mortality index in 1982-2008 with more than 20% probability of the index exceeding 20%. On the other hand, the long-term magnitude and variation of predicted herd mortality index is the lowest in Dirib Gombo despite the observed evidence of its highest morality experience during 2000-2002. This may reflect the fact that relatively large proportion of household's overall livestock loss experienced in Dirib Gombo in such period are due to other factors not captured through vegetation index, which will not be covered under IBLI.[52]

The right panel of Table 5.2 also shows the actuarial fair premium of IBLI, which vary across locations due to differences in the distributions of predicted herd mortality index. In what follows, we use 54 seasons of predicted area averaged herd mortality indices and the derived fair premium rates to evaluate the performance of IBLI among simulated households.

available insurance policies for several states and important grain crops in the U.S. (http://www.rma.usda.gov/policies/2006policy.html ; http://www.farmdoc.uiuc.edu/cropins/index.html).

[52] Moreover, since these indices are constructed out-of-sample, mismatching between the indices and actual experience may, to some extent, reflects the existence of forecasting errors.

Table 5.2 Summary of IBLI Contracts, Chantarat et al. 2009a

Zone	Location	Predicted Mortality Index (M) (%)				Fair Premium Rate (% Herd Value)				
						Contract Strike				
		Mean	S.D.	P(M>10%)	P(M>20%)	10%	15%	20%	25%	30%
Laisamis	Dirib Gombo	8%	8%	28%	9%	2.5%	1.3%	0.6%	0.3%	0.1%
	Logologo	9%	8%	34%	15%	3.4%	1.8%	0.7%	0.1%	0.1%
Chalbi	Kargi	9%	9%	38%	11%	3.3%	1.6%	0.9%	0.4%	0.2%
	North Horr	9%	11%	34%	21%	4.3%	2.8%	1.5%	0.7%	0.3%

5.4 Analytical Framework

We first elaborate a dynamic model with bifurcations in herd accumulation, highly stylized to household herd data in our northern Kenya setting. This model resembles other models of poverty traps[53] in the sense that it creates multiple welfare equilibria – at least one of which is associated with low welfare. While a growing empirical literature has exposed several sources of such nonlinearities within the pastoral system in this region and identified critical herd size thresholds below which a decumulation of herds to a low-level poverty trap equilibrium ensues (Lybbert et al. 2004; McPeak 2004; Barrett et al. 2006; Santos and Barrett 2007), in what follows we impose a realistic consumption requirement to elaborate such herd size threshold in our setting. As will be clear, the presence of this threshold, through its effect on herd dynamics, can change the valuation of IBLI conditional on the current herd size.

5.4.1 A Stylized Model of Bifurcated Livestock Dynamics

Livestock is considered the main productive asset among pastoralists, and since economic activities in this setting revolve around livestock asset, we use livestock as a

[53] Banerjee and Duflo (2004), Azariadis and Stachurski (2005), Bowles et al. (2006), Carter and Barrett (2006) provide excellent summaries of that literature.

standard unit in our model. We denote the herd in the aggregate livestock unit (TLU) realized by household *i* in location *l* at the beginning of season *t* (and so at the end of season *t-1,* where seasons alternate within a year between LRLD and SRSD) as H_{ilt}. Herd dynamics are largely governed by various stochastic processes: the rate of biological reproduction, denoted by $\tilde{b}_{ilt}$, the gross non-biological herd recruitment rate, $\tilde{i}_{ilt}$ (which includes purchases, borrowed animals, transfers in, etc.), the gross herd offtake rate, $\tilde{o}_{ilt}$ (which includes slaughters, sales, transfers out, etc.) and the herd mortality rate, $\tilde{M}_{ilt}$.

Pastoralists rely on livestock as their main source of basic consumption – food from milk produced, slaughtered meat as well as income from sales of livestock and livestock product that can be used to purchase other consumable goods. And so the important determinant of herd dynamics reflecting the necessary seasonal offtake of livestock, is the subsistence consumption, denoted by H^c, which covers fixed amount of the necessary consumption for every member of the household per season.

Herd reproduction, mortality and the behavioral process that determines herd offtake and recruitment decisions are also dependent on the variability and risks inherent in the system. There are two main sources of risk and variability affecting livestock dynamics in this setting. The main covariate component in household's asset risks, driven particularly by rangeland condition, and so is characterized by the constructed set of vegetation index $ndvi_{lt}$ observed prior to and throughout the season *t* in each location *l* with probability distribution $f(ndvi_{lt})$. This component of risk is thus covered by IBLI. Each household also faces other component of risks, ε_{ilt}, uncorrelated with the former covariate component, characterized by a probability distribution $h(\varepsilon_{ilt})$ and so uncovered by IBLI. This latter component includes mainly idiosyncratic component experienced by specific households – such as conflict, raiding, predation, accident, etc. – as well as other non-drought but covariate risk –

such as disease outbreaks – which is shown empirically to be relatively small comparing to the covariate component. Both sources of risks affect herd accumulation in this model directly through stochastic livestock mortality and reproduction, and indirectly through other livestock transaction in the form of risk response and coping.

Together these processes comprise the elements of the net stochastic herd growth rate in period *t*, which nets out herd offtake and mortality rates from the reproduction and herd recruitment rates so that the seasonal herd accumulation can be characterized by

$$\widetilde{H}_{ilt+1} = \begin{pmatrix} 1 + \widetilde{b}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}, H_{ilt}) + \widetilde{i}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}, H_{ilt}) \\ - Max\left\{ \widetilde{o}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}, H_{ilt}), \dfrac{H^c}{H_{ilt}} \right\} - \widetilde{M}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}) \end{pmatrix} \cdot H_{ilt} \tag{5.3}$$

where the stochastic herd $\widetilde{H}_{ilt+1}$ is to be realized at the end of period *t.* And apart from the direct impact from shocks, the reproduction and net offtake rates are shown empirically to vary greatly by household's beginning herd size, H_{ilt}. Note that we abstract here from modeling each of these seemingly complicated livestock reproduction and transaction choices, but we rather calibrate this growth function based on the choices observed in our household-specific dynamic data.

This growth function is assumed to be continuous, equal to zero when the beginning herd size is zero and bounded from below at zero. Equation (5.3) thus imply nonlinearities in herd accumulation generated here by the consumption requirement H^c, which imposes a regressive fixed cost rate – inversely proportionate to the beginning herd – on the rate of return on livestock asset. Given the fixed consumption required, households with smaller herd sizes must consume a larger portion of their herd with decumulation commencing where net herd growth falls below the minimum consumption required rate per season.

The resulting nonlinearity in net herd growth implies a bifurcation in herd accumulation characterized by at least one (subsistence-consumption driven) threshold $H^{*}(H^{c})$ above which expected herd gradually evolves to a high-level equilibrium and below which expected herd steadily falls to a poverty trap equilibrium. Equation (5.3) can be re-written with some nonlinear net herd growth function $\eta(\cdot)$ such that the expected net herd growth conditional on herd size is bifurcated around the critical herd threshold $H^{*}(H^{c})$:

$$\widetilde{H}_{ilt+1} = \eta\left(ndvi_{lt}, \varepsilon_{ilt}, H_{ilt}\right) \quad \text{where} \quad \begin{array}{l} E\eta'_{H_{ilt}}(\cdot) < 0 \ \text{ if } \ H_{ilt} < H^{*}(H^{c}) \\ E\eta'_{H_{ilt}}(\cdot) \geq 0 \ \text{ if } \ H_{ilt} \geq H^{*}(H^{c}). \end{array} \tag{5.4}$$

Imposing the subsistence consumption at 0.5 TLU per season per household,[54] Figure 5.2 illustrates the nonlinear expected net herd growth estimated nonparametrically[55] for this economy using observed household's herd data (birth, mortality, purchase, exchange, sale, slaughter and transfer rates) in 2000-2002 and 2007-2008. This pattern implies the bifurcated herd threshold at around 15-18 TLU per household, below which herds are expected to fall into negative growth trajectory and so collapse overtime at rates inversely proportionate to the herd size. In addition, there are potentially two stable equilibria of 0 TLU, where household slowly collapse out of pastoralism and at the high level of herd at 55-60 TLU, beyond which herds start to reduce again. These findings are in line with Lybbert et al. (2004), McPeak (2004), Barrett et al (2006) and Santos and Barrett (2006).[56]

[54] Previous survey work (McPeak 2004) has shown that average livestock offtake for consumption for a household is averaged lightly less than one goat sale a month. According to FAO (1992), five goats (with 20 kilogram of meat equivalently to 5000 gram of protein) for an average family of three for a 6-month season will provide 46 gram of protein per day per individual (comparing to the recommended daily intake (RDI) of 50 gram of protein per day per individual).

[55] The function is estimated using Epanechnikov kernel with rule-of-thumb optimal bandwidth.

[56] Lybbert et al. (2004) and Santos and Barrett (2007) found the bifurcate threshold in 15-20 TLU range and the high-level stable equilibrium at 40-75 herd range depending on the methodology used among Boran pastoralist in southern Ethiopia. Barrett et al (2006) found this pattern in some of PARIMA sites

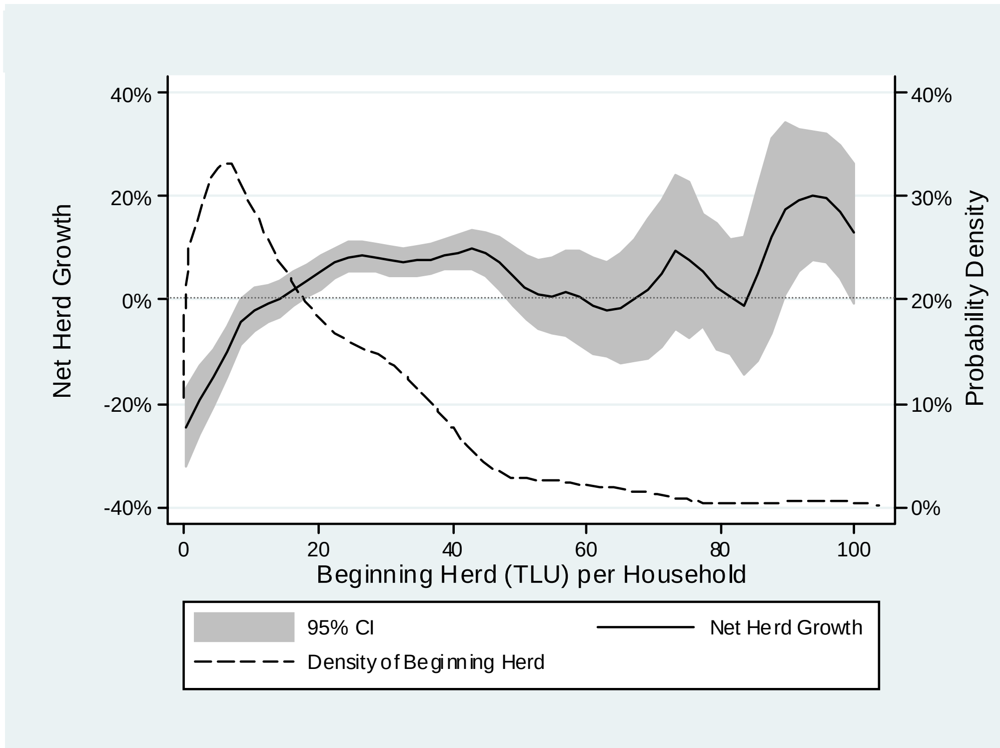

Figure 5.2 Nonparametric Estimations of Expected Net Herd Growth Rate

Household *i* derives their intertemporal utility based on a simplified version of Constant Relative Risk Aversion (CRRA) utility defined over livestock wealth as

$$U\left(H_{ilt}, \widetilde{H}_{ilt+1}(H_{ilt}), \ldots, \widetilde{H}_{ilt+\tau}(H_{ilt}), \ldots\right) = E^t\left(\sum_{\tau=t}^{\infty} \delta^{\tau-t} u(H_{il\tau})\right) \tag{5.5}$$

where $$u(H_{il\tau}) = \frac{\widetilde{H}_{il\tau}^{1-R_i}}{1-R_i}$$

$0 < R_i \leq 1$ is the Arrow Pratt coefficient of relative risk aversion and $\delta \in (0,1)$ is the discounted factor. And for a stockless household, without restocking, they will have to

with the critical threshold of 5-6 TLU per capita and a high stable herd level at around 10 TLU per capita. McPeak (2004) estimated net herd growth function using fixed effect dummy regression in the overlapping sites and found that the net herd growth would become negative beyond a herd threshold of 35-40 TLU.

undeniably exit the pastoral livelihood and thus to enter into another livelihood yielding subsistent return that potentially traps them in irreversible chronic poverty.[57] Because livelihoods of pastoralists in this economy rely on livestock, there is a direct link between herd and welfare dynamics. And so using household utility framework defined over livestock wealth allows us to explore the welfare impact of asset shocks and IBLI, as well as, household's insurance decision given their risk preferences.

A certainty equivalent growth rate of any stochastic herd dynamics is defined as a constant net herd growth rate with respect to the initial herd, H_{ilt} , that yields the same intertemporal utility as the expected intertemporal utility obtained from the stochastic herd dynamics. Specifically, the certainty equivalent growth rate of the stochastic herd dynamics, $\left\{\widetilde{H}_{il\tau}\right\}_{\tau=t+1}^{T}$ can be denoted by η_{il}^{c} and characterized as[58]

$$U\left(\eta_{il}^{c}H_{ilt},...,\eta_{il}^{c}H_{ilt}\right)=U\left(\widetilde{H}_{ilt+1}(H_{ilt}),\widetilde{H}_{ilt+2}(H_{ilt}),...,\widetilde{H}_{ilT}(H_{ilt})\right) \tag{5.6}$$

Therefore, an improvement in the certainty equivalent herd growth rate of the insured herd dynamics relative to that of the uninsured dynamics, $\eta_{il}^{cI}-\eta_{il}^{cNI}$, thus could represent a measure of IBLI performance in improving welfare dynamics of the insured household. And so household's risk preference becomes one of the key determinants of IBLI performance.[59]

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[57] Evidence showed that those who dropped out of pastoral system tended to live their subsistence life in town relying on food aid, casual labor and small-scale petty trading. Those involved high-return non-livestock livelihood still maintain livestock in their diversified livelihood portfolio (McPeak and Little 2005; Doss et al. 2008).

[58] If $\delta=1$, (5.6) can be written in a general characterization as $U(\eta_{il}^{c}H_{ilt})=EU(\widetilde{H}_{ilt+\tau}^{I}(H_{ilt}))$.

[59] An increase in certainty equivalent herd growth rate with respect to IBLI relative to without IBLI directly reflects a positive risk premium growth rate associated with IBLI, which can also serve as an indicator of household's potential demand for such contract specification. By the same token, household's maximum willingness to pay for a particular IBLI contract can be derived by searching for the ρ_{lt}^{a} that drives risk premium growth rate to zero.

5.4.2 Managing Mortality Risk with Index Based Livestock Insurance

IBLI compensates for covariate livestock mortality loss based on the predicted herd mortality index in each location, $\hat{M}(ndvi_{lt})$. For simplicity, we assume that the pastoral household insures either all or none of their entire beginning herd each season, which enables us to compare fully insured herds under several contract specifications against the case of no insurance. The insured herd sixe realization to be realized at the end of coverage season t for a household in location l can thus be written as.

$$\widetilde{H}^{I}_{ilt+1} = \left(1 + \widetilde{g}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}, H_{ilt} \mid H^{c}) - \widetilde{M}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}) + \pi_{lt} - \rho^{a}_{lt}\right) \cdot H_{ilt} \qquad (5.7)$$

IBLI thus reduces expected net herd growth in good seasons, when indemnity payments are not made but households have paid the premium. However, IBLI should at least partially compensate for losses during periods of substantial covariate herd mortality. For any contract $\left(M^{*}, \hat{M}(ndvi_{lt})\right)$, one of the key determinants of the effectiveness in managing livestock mortality risk is thus the presence of basis risk, which reflects to the degree to which IBLI under – or over – compensates for the insured's mortality loss. According to (5.1) and (5.7), basis risk depends on correlations between the predicted area-average mortality index, $\hat{M}_{lt}(ndvi_{lt})$, and the individual-specific mortality rate, $\widetilde{M}_{ilt}(ndvi_{lt}, \varepsilon_{ilt})$. More concretely, IBLI performance improves the larger is the proportion of predictable covariate loss in a household's individual mortality loss, and the more closely the household's loss experience co-moves with the predicted herd mortality index in its location.

As the basis for further household-level analysis, we disaggregate the household-specific mortality rate into a beta representation form of the hedgable predicted mortality index. Specifically, household-specific herd mortality

$\widetilde{M}_{ilt}(ndvi_{lt}, \varepsilon_{ilt})$ is orthogonally projected onto the predicted area-average mortality index as[60]

$$\widetilde{M}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}) = \mu_{il} + \beta_i \left(\hat{M}_{lt}(ndvi_{lt}) - \hat{\mu}_l\right) + \varepsilon_{ilt} \tag{5.8}$$

where $E(\varepsilon_{ilt}) = 0$, $Cov(\hat{M}_{lt}(ndvi_{lt}), \varepsilon_{ilt}) = 0$ and $Var(\varepsilon_{ilt}) = \sigma_{il}^2 I$. Here μ_{il} reflects household i's long-term average mortality rate, which implicitly contains household-specific characteristics that determine their livestock loss (e.g., herding ability), $\hat{\mu}_l$ is the long-term mean of the predicted mortality index for location l and ε_{ilt}, as always, reflects other losses that are not correlated with the covariate component captured by the index.

This beta representation allows us to distinguish various distinctive but interrelated household-specific basis-risk determinants, $\{\beta_i, \varepsilon_{ilt}, \mu_{il}\}$. The coefficient β_i measures the sensitivity of the household's mortality experience to the predicted herd mortality index in their area. $\beta_i = 1$ represents the case in which household i's deviations of livestock losses from its long-term average are, on average perfectly explained by those of the index, while $\beta_i = 0$ corresponds to the case, where these two series are independent. If the household-specific mean mortality μ_{il} is relatively similar to the location-specific mean predicted mortality rate $\hat{\mu}_l$, then the closer is β_i to one, the better will the predicted mortality index explain household's losses, and so the lower is the basis risk. And so such pastoralists with β_i lower (greater) than one will tend to over (under)- insure their herd mortality losses using IBLI.

The risk component ε_{ilt} reflects the relative proportion of household's overall losses that are not manageable by IBLI. The greater its dispersion around zero, the larger the basis risk. Other household-specific characteristics that affect long-term mean mortality, μ_{il}, also determine the degree of basis risk with respect to IBLI.

[60] Miranda (1991) and Mahul (1999) also use variant of this specification.

Holding other things equal, IBLI will, on average, under (over) compensate households with high (lower) long-term mean mortality relative to the long-term mean predicted drought-related mortality in their area. Variation in these key basis risk determinants determine the risk management effectiveness of any IBLI contract specification $\left(M^*, \hat{M}(ndvi_{lt}), \rho_{lt}^a\right)$.

5.4.3 Evaluation of IBLI Performance

The proposed expected utility criterion in the form of certainty equivalent growth rate of the insured herd dynamics relative to that of the uninsured herd thus allows us to evaluate the average impact of IBLI on the entire herd dynamics, in contrast to the current literature, which concentrates on static impact analysis.[61] As IBLI performance in the initial insured seasons could determine the performance in the latter seasons through the reinforcing impact of herd dynamics,[62] we evaluate IBLI over many sets of seasons (with different initial seasonal outcomes), which allows us to take into account different possible impacts on herd dynamics.

Given the current setting of bifurcated herd dynamics, IBLI's performance will depend on a household herd size relative to critical herd threshold. To show this analytically, we simplify this dynamic setting by discretizing the nonlinear net herd growth in (5.4) into an additive form:

[61] There are two parallel approaches that are widely used for evaluation of index insurance; another approach concentrates on measuring improvements in the distribution of the insured outcome based on mean-variance measures, e.g., coefficient of variation, value at risk and downside risk measures, (Skees et al. 2001; Turvey and Nayak 2003; Vedenov and Barnett 2004; among others). But since they disregard the insuree's risk preferences, these measures may, however, overstate the benefit of insurance as the insuree's decision is based on expected utility calculation (Fishburn 1977; Breustedt et al. 2008).

[62] For example, if IBLI fails to protect household from falling into the herd decumulation trajectory during the very first seasons, its performance in the latter seasons could also be low as household might already collapse deeply toward irreversible destitution.

$$\widetilde{H}_{ilt+1} = \left(A(H_{ilt}) + B(ndvi_{lt}, \varepsilon_{ilt})\right)H_{ilt} \qquad \text{such that} \tag{5.9}$$

$$\begin{aligned} A(H_{ilt}) &= \eta_L \ \text{ if } H_{ilt} < H^* && \text{and} \quad & B(ndvi_{lt}, \varepsilon_{ilt}) &= \eta_G + \varepsilon_{ilt} \ \text{ with probability } P \\ &= \eta_H \ \text{ if } H_{ilt} \geq H^* && & &= \eta_B + \varepsilon_{ilt} \ \text{ with probability 1-} P \end{aligned}$$

where $A(\cdot)$ represents the component of herd growth rate that is conditional on initial herd size relative to the critical threshold with $0 < \eta_L < 1$ and $\eta_H > 1$. $B(\cdot)$ represents the stochastic component of herd growth written in an additive form of the covariate component captured by NDVI ($\eta_G > 0$ in a good season – when $\hat{M}(ndvi_{lt}) \leq M^*$ with probability $P = \int_0^{M^*} \hat{M}(ndvi_{lt}) df(ndvi_{lt})$ – and $\eta_B < 0$ in the bad season occurred with probability $1 - P$), and the uncovered, somewhat idiosyncratic, component with $E(\varepsilon_{ilt}) = 0$. Assuming, for simplicity, that $P\eta_G + (1-P)\eta_B = 0$, this implies the expected herd dynamics:

$$E\widetilde{H}_{ilt+1} = \eta_i H_{ilt} \qquad \text{where} \quad \begin{aligned} \eta_i &= \eta_L \ \text{ if } H_{ilt} < H^* \\ \eta_i &= \eta_H \ \text{ if } H_{ilt} \geq H^*. \end{aligned} \tag{5.10}$$

This simplifies setting allows us to derive recursively two stable intertemporal welfare levels:

$$U\left(H_{ilt}, H_{ilt+1}\left(H_{ilt}\right), \ldots\right) = \frac{u\left(H_{ilt}\right)}{1 - \delta\eta_i^{1-R_i}} \qquad \text{where} \quad \begin{aligned} \eta_i &= \eta_L \ \text{ if } H_{ilt} < H^* \\ \eta_i &= \eta_H \ \text{ if } H_{ilt} \geq H^*. \end{aligned} \tag{5.11}$$

with $0 < \eta_L < 1$ eventually leading those with $H_{ilt} < H^*$ into a long-run equilibrium herd size closed to zero.

We consider the expected impact of IBLI on herd dynamics in a simple setting when pastoralists can insure all of their herds at period *t* with an IBLI contract priced at ρ_{lt} that pays π_{lt} in a bad season with probability $1 - P$ and pays nothing during a good season with probability P. Holding risk preferences and other basis risk determinants constant, the effect of an IBLI contract obtained at period t on pastoralist's herd and welfare dynamics in the continuing periods $t+1,...,T$ can be shown to vary across pastoralists with different beginning herd sizes, which could determine how IBLI alters their livestock dynamics. Four distinct cohorts emerge.

(1) The first cohort consists of pastoralists with beginning herd size too far beneath to grow past H^* by the end of the season, even in a good season and without insurance, $(\eta_L + \eta_G)H_{ilt} < H^*$. For this cohort, IBLI could not alter their herd dynamics. Thus IBLI only provides typical insurance in reducing the probability of herd loss during a bad season, while the premium payment speeds up their herd decumulation during good seasons. By (5.6), their IBLI valuation is the same relative to the standard case with no asset bifurcation:

(5.12)

No IBLI: $$\frac{u\left(\eta_{il}^{cNI1} H_{ilt}\right)}{1-\delta\eta_L^{1-R_i}} = P\frac{u\left((\eta_L+\eta_G)H_{ilt}\right)}{1-\delta\eta_L^{1-R_i}} + (1-P)\frac{u\left((\eta_L+\eta_B)H_{ilt}\right)}{1-\delta\eta_L^{1-R_i}}$$

W/ IBLI: $$\frac{u\left(\eta_{il}^{cI1} H_{ilt}\right)}{1-\delta\eta_L^{1-R_i}} = P\frac{u\left((\eta_L+\eta_G-\rho_{lt})H_{ilt}\right)}{1-\delta\eta_L^{1-R_i}} + (1-P)\frac{u\left((\eta_L+\eta_B+\pi_{lt}-\rho_{lt})H_{ilt}\right)}{1-\delta\eta_L^{1-R_i}}$$

Therefore:

$$\begin{aligned}\eta_{il}^{cI1} - \eta_{il}^{cNI1} &= \left(P\cdot(\eta_L+\eta_G-\rho_{lt})^{1-R_i} + (1-P)(\eta_L+\eta_B+\pi_{lt}-\rho_{lt})^{1-R_i}\right)^{R_i-1} \\ &\quad - \left(P\cdot(\eta_L+\eta_G)^{1-R_i} + (1-P)(\eta_L+\eta_B)^{1-R_i}\right)^{R_i-1}.\end{aligned}$$

Household's valuation and so potential demand for IBLI (represented by a positive risk premium growth rate) will depend on the extent to which IBLI, imperfectly, compensates for the insured's losses. And since households this cohort end up converging to the low-level equilibrium with or without IBLI with very low η_L, IBLI performance in their herd dynamics is expected to be the low.

(2) The second cohort consists of pastoralists expecting to grow their herds. Their beginning herd sizes are modestly above H^*. These allows them to grow if the season is good and without insurance. However, paying the insurance premium without receiving indemnity payment in a good season will drop them beneath H^* so that $H^* < (\eta_L + \eta_G)H_{ilt} < H^* + \rho_{lt} H_{ilt1}$. Because IBLI shifts down their herd growth trajectory, the risk premium rate is therefore taxed by $\left(\frac{1-\delta\eta_L^{1-\theta_i}}{1-\delta\eta_H^{1-\theta_i}}\right) > 1$. The valuation of IBLI is lower than would be the case without bifurcation in herd dynamics. This slightly more risk-loving decision holds true regardless of risk preferences. And so

(5.13)

$$\eta_{il}^{cI2} - \eta_{il}^{cNI2} = \left(P \cdot (\eta_H + \eta_G - \rho_{lt})^{1-R_i} + (1-P)(\eta_H + \eta_B + \pi_{lt} - \rho_{lt})^{1-R_i}\right)^{R_i - 1} - \left(\left(\frac{1-\delta\eta_L^{1-\theta_i}}{1-\delta\eta_H^{1-\theta_i}}\right) \cdot P \cdot (\eta_H + \eta_G)^{1-R_i} + (1-P)(\eta_H + \eta_B)^{1-R_i}\right)^{R_i - 1}$$

(3) The third cohort is an interesting one consisting of pastoralists with beginning herd sizes slightly above but still vulnerable to the risk of falling below H^*. For this cohort, IBLI protects them from falling below H^* and their herd after paying insurance premium still allows them to sit at above H^*. Their beginning herds are thus conditioned by $(\eta_L + \eta_G)H_{ilt} \geq H^* + \rho_{lt} H_{ilt}$, $H^* - (\pi_{lt} - \rho_{lt})H_{ilt} < (\eta_L + \eta_B)H_{ilt} < H^*$. Since IBLI preserves their growth trajectory, the factor $\left(\frac{1-\delta\eta_H^{1-R_i}}{1-\delta\eta_L^{1-R_i}}\right) < 1$ increases their IBLI valuation relative to the case without bifurcation dynamics. The willingness to pay for IBLI from this cohort is among the highest of the four cohorts according to

(5.14)

$$\eta_{il}^{cI3} - \eta_{il}^{cNI3} = \left(P \cdot (\eta_H + \eta_G - \rho_{lt})^{1-R_i} + (1-P)(\eta_H + \eta_B + \pi_{lt} - \rho_{lt})^{1-R_i}\right)^{R_i - 1} - \left(P \cdot (\eta_H + \eta_G)^{1-R_i} + \left(\frac{1-\delta\eta_H^{1-R_i}}{1-\delta\eta_L^{1-R_i}}\right) \cdot (1-P) \cdot (\eta_H + \eta_B)^{1-R_i}\right)^{R_i - 1}$$

(4) The last cohort consists of large-scaled pastoralists with large herd sizes that even without insurance are not expected to fall below the critical herd threshold after covariate shocks; $(\eta_H + \eta_B)H_{ilt} \geq H^*$. IBLI thus would not alter their herd dynamics, just like the first cohort (with the smallest herds). As these larger herd sizes have expected net herd growth, η_H, their valuation of IBLI should be significantly more than those in the first cohort according to

$$\eta_{il}^{cI4} - \eta_{il}^{cNI4} = \left(P \cdot (\eta_H + \eta_G - \rho_{lt})^{1-R_i} + (1-P)(\eta_H + \eta_B + \pi_{lt} - \rho_{lt})^{1-R_i}\right)^{R_i - 1} - \left(P \cdot (\eta_H + \eta_G)^{1-R_i} + (1-P) \cdot (\eta_H + \eta_G)^{1-R_i}\right)^{R_i - 1} \tag{5.15}$$

The expected threshold-based performance of IBLI under the presence of bifurcations in wealth dynamics are also found in Lybbert and Barrett (Forthcoming) in a different poverty trap model. The above illustration thus implies that if herd threshold is well perceived by households in this system, variation in IBLI valuation conditional on beginning herd size relative to the bifurcated threshold should emerge. And so cohort three and four are therefore expected to represent the main source of demand for IBLI in this setting.

In what follows, we simulate households' herd dynamics and these key performance determinants in order to explore the effectiveness of IBLI contracts.

5.5 Empirical Estimations and Simulations

The main component in estimating and simulating herd dynamics is the net herd growth rate in (5.3). We estimate the non-mortality component separately from the mortality component as we are particularly interested in estimating the key basis risk determinants directly from the correlations between individual household's livestock mortality and the location-specific predicted herd loss index that triggers IBLI payout expressed in (5.8).

We first estimate non-mortality component of the seasonal livestock growth function in (5.3) by imposing subsistence consumption at 0.5 TLU per household per season. Four seasons of dynamic herd growth and transactions in PARIMA in 2000-2002 and two seasons of 2007-2008, calculated from the mid-2008 household survey data, are pooled in the estimation to increase temporal variability with working assumption that the expected growth function is stable across 2000-2008. Kernel-weighted local polynomial regression[63] is used to estimate two nonparametric relationships between the non-mortality herd growth rates[64] and household's beginning TLU herd sizes conditional on whether a season is a good season or a bad one based on observed seasonal NDVI data according to Chantarat et al (2009a). The two estimated non-mortality growth functions conditional on the vegetation condition will be used in the simulation of herd dynamics. They are plotted in Appendix B.1.

Next, we concentrate on livestock mortality rate and so estimate the relationship between household-specific mortality rates and the location-average predicted mortality index described in (5.8). We pool four seasons of household-specific mortality rates across the four locations in PARIMA during 2000-2002. A linear relationship between deviations of the two from their long-term means is then estimated using a random coefficient model with random effects at the slope coefficient. This model thus allows us to take into account variations of slope coefficients across households and is estimated using maximum likelihood.[65]

[63] Epanechnikov kernel function is used and the optimal bandwidth is chosen according to Silverman's Rule of Thumb.

[64] Livestock accounting variables used in these estimations are birth, purchase, borrow, exchange, sale, slaughter, lend and transfer.

[65] Generally, estimations of models of beta-representation, e.g., in CAPM model, in financial econometrics rely on the seemingly unrelated regression model for sector (i)-specific equations, which allows for unrestricted structures of disturbance (e.g., due to potentially cross-sectional correlations). In

The estimated beta coefficient thus represents the degree of sensitivity of household's mortality loss to the predicted covariate mortality index for their location. It is, however, reasonable to assume that there may still be other covariate but unpredicted components in addition to the idiosyncratic component in the model's disturbances, which can potentially result in cross-sectional correlations. In an attempt to disaggregate these two components in the disturbances, the predicted seasonal household-specific residual $\hat{\varepsilon}_{ilt}$ is projected onto its location-specific mean each season $\overline{\varepsilon}_{lt}$.[66] And so the model we estimate can be summarized as

$$\widetilde{M}_{ilt}(ndvi_{lt}, \varepsilon_{ilt}) - \mu_{il} = \beta_i \left(\hat{M}_{lt}(ndvi_{lt}) - \hat{\mu}_l\right) + \varepsilon_{ilt} \qquad (5.16)$$

$$\varepsilon_{ilt} = \beta^{\varepsilon} \overline{\varepsilon}_{lt} + e_{ilt}$$

where $\beta^{\varepsilon} \overline{\varepsilon}_{lt}$ represents the covariate component in the unpredicted mortality loss with degree of co-variation measured by β^{ε}, and e_{ilt} represents household's idiosyncratic mortality loss with $E(e_{ilt}) = 0$, $E(e_{ilt} e_{jlt}) = 0$ if $i \neq j$, and $Var(e_{ilt}) = \sigma_{il}^2 I$. The estimation results, which allow us to estimate household's basis-risk-determining parameters and other key characteristics in $\{\beta_i, \varepsilon_{ilt}, \mu_{il}, H_{ilt}, \beta_i^{\varepsilon}, e_{ilt}\}$, are reported in Appendix B.2.

Disaggregating the estimated parameters by location, we show in Figure 5.3 the significant variations in location-specific distributions of household betas, as well as, the unpredicted component of mortality losses ε_{ilt}. The two distributions are most dispersed in Dirib Gombo relative to other locations implying the potentially great variations in basis risk experience and so in performance of IBLI among households in this location. The beta distributions seem to nicely center around one in Dirib Gombo,

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our case, we do not have enough longitudinal observations of individual households to apply that model.

[66] The intercept for this model is zero by construction.

slightly above one at 1.1 in Logologo, slightly lower at 0.7 in Kargi but a lot lower at around 0.4 in North Horr despite its lower dispersion. This implies that households in the relatively more arid locations, e.g., Kargi and especially North Horr, will tend to over-insure their herd losses using full coverage IBLI, on average.

And in sharp contrast to Dirib Gombo, the particularly low dispersion in the distributions of unpredicted mortality loss, especially in North Horr, indicates that covariate losses captured by the index are a key determinant for variation in livestock mortality in these areas and speaks to the potential of IBLI to protect the insured against asset loss.

For the purpose of simulations, we then estimate parametrically the best fit joint distributions of the estimated household-specific characteristics $\{\beta_i, \varepsilon_{ilt}, \mu_{il}, H_{ilt}, \beta_i^{\varepsilon}, e_{ilt}\}$ by location. Estimations were done using best fit functions in @Risk program, which allows us to specify correlation matrix that captures pairwise relationships between these variables, and the upper or lower limits of the distributions. The best-fit distributions – range from normal, logistic, lognormal, loglogistic and extreme value distributions – are then chosen based on the chi-square goodness of fit criterion. The estimation results are reported in Appendix B.2.

From the estimated distributions, we then proceed to simulate herd dynamics of 500 representative households in each location as follows. For each location, we randomly draw 500 combinations of household-specific $\{\beta_i, \beta_i^{\varepsilon}, \mu_{il}, H_{ilt}\}$ from the joint distributions – each of which represents a simulated representative household. For each simulated household, we then randomly draw 54 seasons of idiosyncratic components of mortality loss, e_{ilt}, from the location-specific distributions.[67] We also randomly draw 54 seasons of location-average unpredicted mortality losses, $\bar{\varepsilon}_{lt}$,

[67] We use location-specific distribution of e_{ilt} since we do not have enough individual data to simulate the individual-specific distribution.

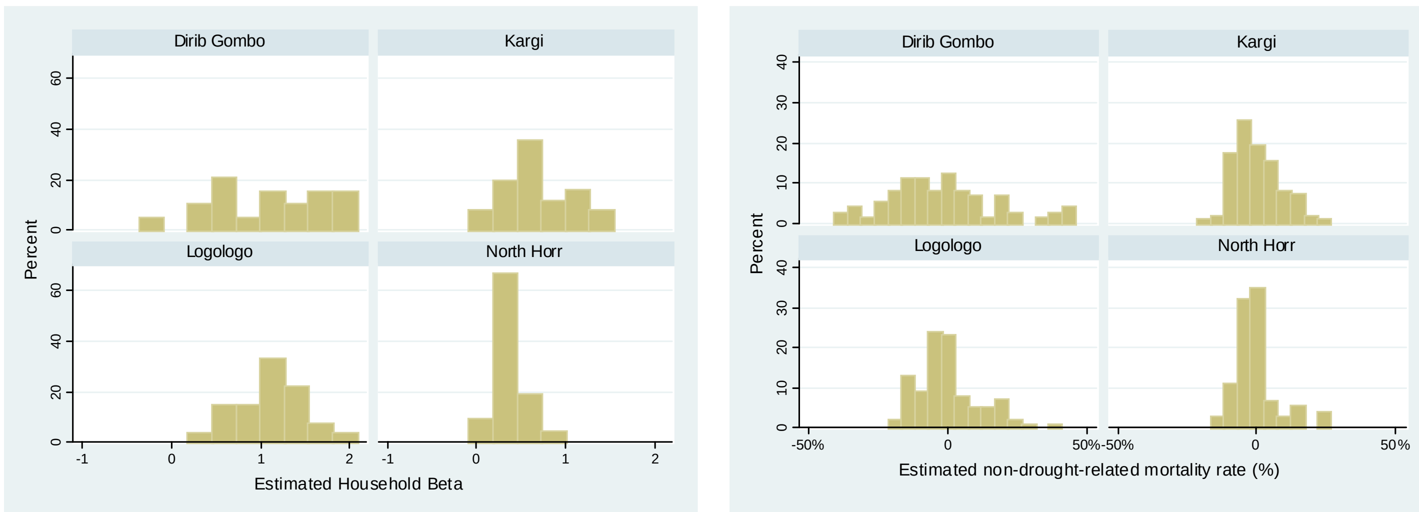

Figure 5.3 Estimated Household-Specific Beta and Non-Drought-Related Mortality Rate, Random Coefficient Model (2000-2002)

from one of the four estimated values from (5.16) based on the four seasons of observed data for each location. With $\{\beta_i^{\varepsilon}, e_{ilt}, \bar{\varepsilon}_{lt}\}$, we can then derive 54 seasons of unpredicted mortality losses, ε_{ilt}, for each simulated household. Fifty four seasons of location-specific predicted mortality index, $\hat{M}(ndvi_{lt})$, and the associated long-term mean, $\hat{\mu}_{lt}$ are then assigned to each simulated household. So according to (5.8), we can construct 54 consecutive seasons of household-specific mortality rates using $\{\beta_i, \varepsilon_{ilt}, \mu_{il}, \hat{M}(ndvi_{lt}), \hat{\mu}_{il}\}$. Appendix B.3 summarize these simulated parameters.

Using the simulated household's beginning herd size, H_{ilt}, and fifty four seasons of vegetation index we can then simulate the household-specific non-mortality component of seasonal herd growth function in (5.3) based on the nonparametric function estimated earlier. Finally, we then use household-specific beginning herd size, non-mortality and mortality components of seasonal growth rates to construct household-specific seasonal herd dynamics based on (5.3)-(5.4). Overall, fifty four consecutive seasons of simulated herd dynamics for 500 representative households in each of the four locations thus serves as the baseline case for evaluation of IBLI.

Figure 5.4 presents the cumulative distributions of baseline household herds (without insurance) during various years for each location. More than 80% of herds collapse toward destitution over time in Dirib Gombo, comparing to less than 10% in North Horr, reflecting the relatively low beginning herd sizes and high seasonal mortality experience in Dirib Gombo relative to others. The bifurcation in livestock accumulation in the simulated herd dynamics can be shown by simply estimating the autoregression in (5.4) for 10-season (5-year) lags. Figure 5.5 plots the results with bifurcated herd threshold around 15-18 TLU. As we pool the observed herd dynamics data across all the study locations in this empirical estimation and simulation, this stylized result thus holds true with the working assumption of uniform herd dynamics across households in these locations.

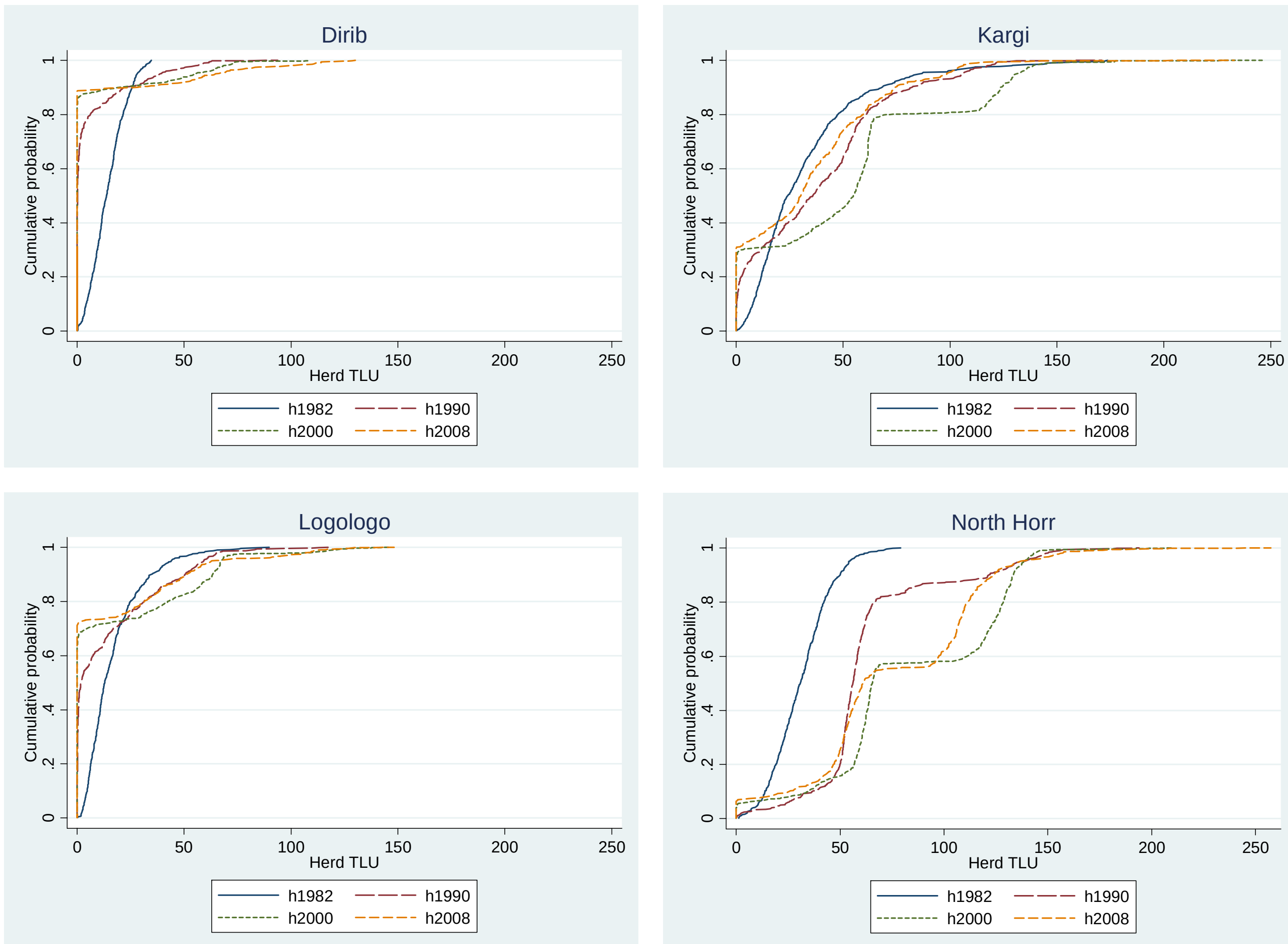

Figure 5.4 Cumulative Distributions of Simulated Herds by Location and Key Years

Figure 5.5 Simulated Bifurcated Herd Accumulation Dynamics, 1982-2008

We also simulate dynamics for 15 stylized pastoralist households with key characteristics, e.g., five different beginning TLU herd sizes $\{5,10,15,20,30\}$ and three levels of beta coefficients $\{0.5,1,1.5\}$ for each of the herd size. Each is assumed to have a long-term mortality rate that resembles the location-specific long-term mean predicted mortality index, and a location-specific uncovered risk component. These stylized households allow us to better study the impact of basis risk determinants and herd sizes on IBLI's effect on herd dynamics.

We are now ready to analyze the effectiveness of IBLI by simply comparing herd dynamics with and without IBLI. We construct 54 pseudo sets of 54 consecutive seasons from the existing vegetation data letting each observation serve as an initial period once in a revolving 54-season sequence with the working assumption that these

54 seasons repeat themselves. This allows us to evaluate performance of IBLI taking into account different possible initial realizations of stochastic range conditions. Note that we choose to construct these pseudo sets of 54-seasons by using the observed historical distribution rather than to randomly simulate them due to infeasibility of estimating empirical distribution of NDVI that can appropriately capture the complex autoregressive structure of the observed series.

Five IBLI contracts with five strike levels of five percent increments from 10-30% are considered. Households are assumed to insure their entire herd. For each contract, we simulate the resulting insured herd dynamics based on (5.7) using the distribution of location-specific seasonal predicted mortality index $\hat{M}(ndvi_{lt})$ and the location-specific premium rate shown in Table 5.2.

As we compute the value of insurance based on the expected utility approach, the certainty equivalent herd growth depends on household discount rates and risk preferences. For simplicity, we assume $\delta = 1$. Household-specific CRRA are simulated based on a simple experimental lottery game run among the households in the June-July 2008 survey. Our risk elicitation game follows the simple method used in Binswanger (1980, 1981); Eckel and Grossman (2002); Barr (2003) and Dave et al. (2007). Households were first given 100 Ksh for participating. Then we introduced five lotteries, which vary by risk and expected return. Respondents were asked if they would use 100 Ksh to play one of the five lotteries for a real prize. If they decided to pay 100 Ksh to play, they were then asked to choose their most preferred lottery to play. A fair coin was then tossed to determine their prize.

Six categorizations of risk aversion associated with six coefficients of relative risk aversion, {0, 0.1, 0.3, 0.4, 0.7, 1}, were derived based on households' choices (Chantarat et al. 2009c). Appendix B.4 summarizes the settings and results of this risk preference elicitation. For each location, we then randomly assign each simulated household with one of the six CRRA based on the observed distributions of CRRA associated with each of the three livestock wealth groups of low, medium and high defined based on the local standards used in the survey sample stratification.

5.6 Effectiveness of IBLI for Managing Livestock Asset Risk

As IBLI performance is earlier elaborated to depend on how it could affect the insured's herd dynamics, we first explore the key patterns of varying IBLI performance conditional on beginning herd sizes that emerge in our simulations. Figure 5.6 depicts some key patterns using Kargi and $\beta = 1$ as an example setting. Panel (a) to (e) each reflect cumulative distributions of uninsured and insured herd sizes for a single household realized over a set of 54 seasons.

Panel (a) shows that performance of IBLI should be minimal for pastoralist with low beginning herd size (e.g., of 5 TLU). IBLI cannot prevent these households from falling into destitution given how far they are beneath the critical herd growth threshold (of roughly 18 TLU). On the other hand, paying an insurance premium each season accelerates herd collapses.[68]

Interestingly, varying patterns of IBLI performance emerge for pastoralists with herd sizes around the critical herd threshold – and so whose herd dynamics are very sensitive to shocks. Panel (b) represents pastoralist with herd size of 15 TLU – immediately at or slightly below the critical threshold – who was hit by big covariate shocks that disrupt his asset accumulation and so place him in the de-cumulating growth path without insurance. But IBLI could imperfectly compensate for such losses and so stabilize the pathway toward growth trajectory. And so because IBLI shifts his

[68] Our model assumes away possible indirect benefits of IBLI, such as its potential to crowd-in finance for ancillary investment and growth. If IBLI crowds in credit access, it may alter the growth trajectory of the least well-off pastoralists as well.

herd dynamics, the improvement of certainty equivalent herd growth associated with IBLI for such pastoralist should, therefore, be relatively higher than under the setting without bifurcation in herd dynamics, holding other things constant.

Panel (c) presents the opposite case commonly emerge in some sets of 54 seasons of pastoralist with the same growing herd size of 15 TLU. For this pastoralist, who may slowly climb toward herd growth trajectory during good vegetative seasons, paying an IBLI premium each season without the occurrence of severe shocks may involve costly suppressing their asset necessary for herd accumulation, which tends to decrease the chance of achieving their expected herd accumulation trajectory (which otherwise could have reached without IBLI). Low IBLI performance should be well expected for this case.

Some IBLI contracts are shown to have significant impacts on those pastoralists with herd sizes modestly above the critical threshold but are still vulnerable to falling into decumulation trajectory due to asset shock. Panel (d) presents a pastoralist with 20 TLU with some specifications of actuarial fair IBLI (e.g., 10% strike contract) that could protect his herd from falling into destitution due to covariate shock. This role of IBLI in stemming the downward spiral of vulnerable pastoralists into destitution should thus result in relatively significant improvement in certainty equivalent herd growth. Therefore, panel (b) to (d) imply that for pastoralists with beginning herd around critical threshold, performance of IBLI can vary a whole lot depending on how IBLI alters the insured's herd growth dynamics.

Panel (e) depicts the common pattern of IBLI performance for pastoralists with beginning herd size relatively far above the critical threshold – e.g. of 30 TLU – even with not much danger of falling into destitution in the absence of a major shock. IBLI contracts provide a typical insurance role by reducing probability of herd falling below the critically low level, while paying for seasonal premium payments out of their herds may as well reduce the chance of reaching extremely large herd. And so the pattern of second-order stochastic dominance of the insured herd sizes relative to the uninsured is uniformly observed among those with large herds. This implies that demand for at least fair IBLI should be highly expected among the risk averse wealthier herders, holding other things equal.

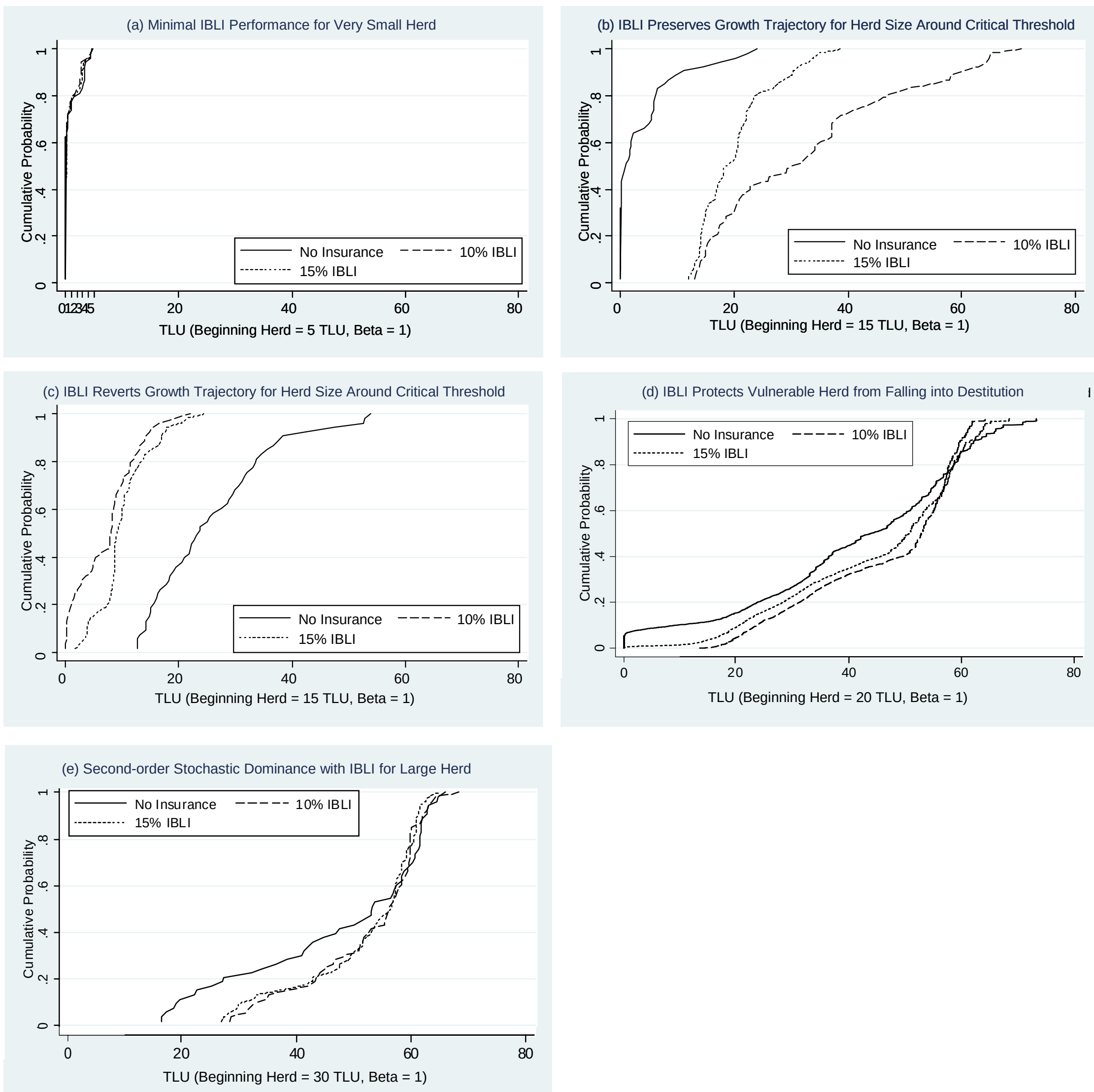

Figure 5.6 IBLI Performance Conditional on Beginning Herd Size, Pastoralists in Kargi, 54 Seasons

The ex ante wealth impacts on IBLI performance shown in Figure 5.6, however, do not imply a specific herd threshold that determine IBLI's impact on herd dynamics, as we still hold constant other household- and location-specific characteristics that determine exposures to basis risks associated with IBLI.[69] Holding other things equal, pastoralists with low (high) beta will tend to over (under) insure their herd losses with IBLI, and so they end up paying higher (lower) price for IBLI that offer unnecessarily over-(insufficiently under-) compensations for their losses on average. On one hand, the former case of over-insuring with IBLI may lead to adverse impact as paying high premium costs *ex ante* may suppress resources necessarily for asset accumulation. This is in contrast to the case of under-insuring, where the benefit of lower – but fair – price for partial insurance compensation comes at the cost of potential inadequate protection for their herd losses. These comparable impacts are to be explored in the simulations.

IBLI performance should also vary across locations conditional on the location-specific distributions of uncovered asset risks and the distributions of covariate shock. On average, IBLI performance will be higher in the locations with lower dispersion of uncovered risk. In addition, as we show earlier that paying an IBLI premium for rare – but fair – chance of indemnity payout especially in the early seasons could lead to adverse impact by impeding asset accumulation for some pastoralists with growing herd. IBLI performance is also expected to be higher in the locations with higher probability of insurable covariate losses.

We now consider performance of actuarially fair IBLI contracts conditional on contract specifications and household characteristics. The improvement in certainty equivalent herd growth rate (e.g., equivalently termed as a positive risk premium

[69] And so it is possible for some pastoralists with as high as 40 TLU to still be vulnerable to shock, and so can benefit greatly from IBLI in preserving their growth trajectory.

growth rate) associated with IBLI for 15 stylized households (with individual mean mortality fixed at the location-averaged mean predicted mortality index) in each of the four locations are reported in Table 5.3.[70] Various interesting results emerge.

First, we can observe that IBLI performance varies with beginning herd sizes, the result of which confirms the emerging common patterns shown in Figure 5.6. The performance is minimal for pastoralists with lowest herd sizes (e.g. of 5 TLU) and the highest for those with the herd sizes around critical herd threshold (e.g., 15-20 TLU). These results thus imply that IBLI is not well suited for the poorest in this setting, which are already trapped far beneath the critical herd threshold.

Second, IBLI performance tends to improve as beta increases, holding other things equal. This implies that over-insuring tends to have far larger adverse impact to herd dynamics. Third, IBLI performance is lowest in Dirib Gombo and highest in North Horr, reflecting differences in dispersions of unpredicted asset risk experience and in the distributions of covariate risk covered by IBLI. And lastly, IBLI contract with 10% strike out-performs others, on average, even though the 10% strike contract is more costly than the others. This may reflect the fact that the 10% strike contract could provide greater necessary protection for the household's asset risk.

[70] For simplicity, Table 5.3 only reports certainty equivalent results calculated with respect to the value of constant relative risk aversion of 0.7. Results for other degrees of CRRA are largely similar and can be requested from the authors.

Table 5.3 Increase in Certainty Equivalent Growth Rate, Selected Pastoralists

Strike	Beta = 0.5				Beta = 1				Beta = 1.5			
	DG	LG	KA	NH	DG	LG	KA	NH	DG	LG	KA	NH
Beginning herd = 5 TLU												
10	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%
20	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
30	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Beginning herd = 10 TLU												
10	10%	1%	-35%	-8%	14%	2%	-14%	13%	12%	-3%	8%	28%
20	8%	1%	-17%	5%	7%	1%	2%	17%	5%	0%	10%	22%
30	0%	-7%	-5%	1%	2%	-4%	1%	-2%	1%	-2%	0%	1%
Beginning herd = 15 TLU												
10	11%	8%	13%	39%	15%	22%	18%	42%	26%	35%	46%	53%
20	8%	2%	8%	15%	9%	10%	17%	19%	19%	9%	35%	29%
30	1%	-4%	0%	2%	5%	-5%	4%	1%	8%	-5%	10%	5%
Beginning herd = 20 TLU												
10	8%	2%	8%	17%	17%	17%	37%	46%	10%	28%	53%	56%
20	5%	7%	9%	11%	17%	7%	26%	24%	9%	9%	42%	22%
30	0%	-3%	3%	0%	5%	-4%	6%	1%	4%	-3%	12%	0%
Beginning herd = 30 TLU												
10	6%	-1%	-3%	6%	12%	7%	16%	23%	4%	18%	54%	41%
20	6%	1%	-3%	2%	11%	3%	14%	15%	5%	4%	40%	19%
30	0%	-1%	-1%	0%	1%	-3%	4%	0%	4%	-1%	11%	-1%

Note: An increase in certainty equivalent growth rate is the certainty equivalent growth rate (%) of the insured herd dynamics minus that of the uninsured herd dynamics.

We already observe how variations in household- and location-specific characteristics could individually determine IBLI performance. Next, we explore how variations of these characteristics based on their observed distributions could determine variations of IBLI performance across pastoral populations in these study locations. Table 5.4 first reports the overall averaged performance of actuarially fair IBLI contracts among 500 simulated pastoralists in each of the four studied locations simulated based on the observed heterogeneous distributions.

Table 5.4 IBLI Performance for Overall Locations, 2000 Simulated Pastoralists

Case	Without IBLI			With IBLI							
Strike	Beta	Beginning Herd (TLU)	L-T Mean Herd (TLU)	Fair Premium (%)	Increase L-T Mean Herd (%)	Decrease SV(mean) (%)	Increase in CER Growth Rate (%)				
							r = 0.9	r = 0.7	r = 0.4	r = 0.1	Simulated CRRA
Dirib Gombo											
10	1.1	14.4	6.1	2.5%	15.8%	5.6%	2.6%	2.5%	2.3%	2.1%	2.6%
20	1.1	14.4	6.1	0.6%	7.0%	3.5%	1.4%	1.2%	1.1%	1.0%	1.4%
30	1.1	14.4	6.1	0.1%	1.4%	0.7%	0.2%	0.2%	0.2%	0.1%	0.2%
Logologo											
10	1.1	17.1	14.0	3.4%	14.7%	10.0%	3.9%	3.9%	3.9%	3.7%	3.9%
20	1.1	17.1	14.0	0.7%	4.0%	5.3%	1.6%	1.6%	1.6%	1.5%	1.6%
30	1.1	17.1	14.0	0.1%	-1.6%	-3.4%	-1.4%	-1.4%	-1.5%	-1.5%	-1.4%
Kargi											
10	0.7	32.7	37.9	3.3%	21.3%	13.4%	6.2%	5.9%	5.4%	5.0%	6.0%
20	0.7	32.7	37.9	0.9%	10.4%	11.7%	4.3%	4.0%	3.6%	3.2%	4.1%
30	0.7	32.7	37.9	0.2%	1.0%	5.1%	0.5%	0.4%	0.2%	0.1%	0.4%
North Horr											
10	0.4	31.3	66.5	4.3%	17.8%	17.9%	12.9%	12.7%	12.2%	11.9%	12.1%
20	0.4	31.3	66.5	1.5%	5.5%	10.8%	3.4%	3.2%	2.9%	2.6%	2.9%
30	0.4	31.3	66.5	0.3%	-0.2%	-1.2%	-0.8%	-0.9%	-1.0%	-1.1%	-0.9%

The main results vary across locations as expected. On average, adopting fair IBLI contracts with a 10% strike level results in a 15-21% increase in the long-term mean herd size, and a reduction in downside risk of 6-18%.[71] On average, improvement in certainty equivalent herd growth increases only modestly with the assumed degrees of CRRA as expected. Using the simulated CRRA, it is shown that in general, effective demand for IBLI exists for all locations for IBLI contracts with less than 30% strike with the highest demand being for the 10% strike contract.

[71] These two measures are used widely in the mean-variance evaluation approach of agricultural insurance. Downside risk reduction is measured by semi-variance reduction of the insured herd dynamics with IBLI relative to the uninsured herd. Specifically, semi-variance of the insured herd dynamics over a set of consecutive seasons $t,...,T$, denoted by $\left\{\tilde{H}^{I}_{il\tau}\right\}_{\tau=t+1}^{T}$, relative to some threshold, for example, household's long-term mean herd size $\overline{H}_{il}$, can be well written as $SV_{\overline{H}_{il}}(\tilde{H}^{I}_{il\tau}) = EMax(\overline{H}_{il} - \tilde{H}^{I}_{il\tau}, 0)^2$.

The performance and valuation of IBLI varies markedly across locations, partly due to variation in how well the predicted mortality index captures individual herd losses and partly because of differences in location-specific herd size distributions. More specifically, relative performance across locations can be positively ranked with the location-specific mean beginning herd size (and proportion of large-scaled pastoralists). And though this ranking is also inversely associated with the dispersion of unpredicted asset risk, it is not monotonically associated to the location-specific mean beta. For example, the highest IBLI performance is found in North Horr with the lowest mean beta. This may imply that beginning herd sizes serve as the dominating factor in determining IBLI performance relative to other characteristics.

How will the performance of these actuarially fair IBLI contracts vary across pastoralists in these locations? Figure 5.7 presents the cumulative distributions of the improvement in certainty equivalent growth rates with respect to IBLI contracts calculated with respect to the simulated CRRA among 2000 simulated pastoralists in these four locations. This shows that at least 50% of households in these four locations benefit from IBLI contract with 10% strike (and slightly less proportions for other strike levels) with the positive risk premium growth rates associated with the contract range from almost 0% to 100%. It is clear that the distribution of valuations for 10% contract dominates all other contracts in these locations implying that the 10% strike contract is optimal across the four studied locations. Improvement in certainty equivalent herd growth rate associated with IBLI also conveys important information regarding potential demand for the contracts – e.g., with the existence of potential demand for actuarial fair IBLI with 10% strike thus expected among at least 50% of households.

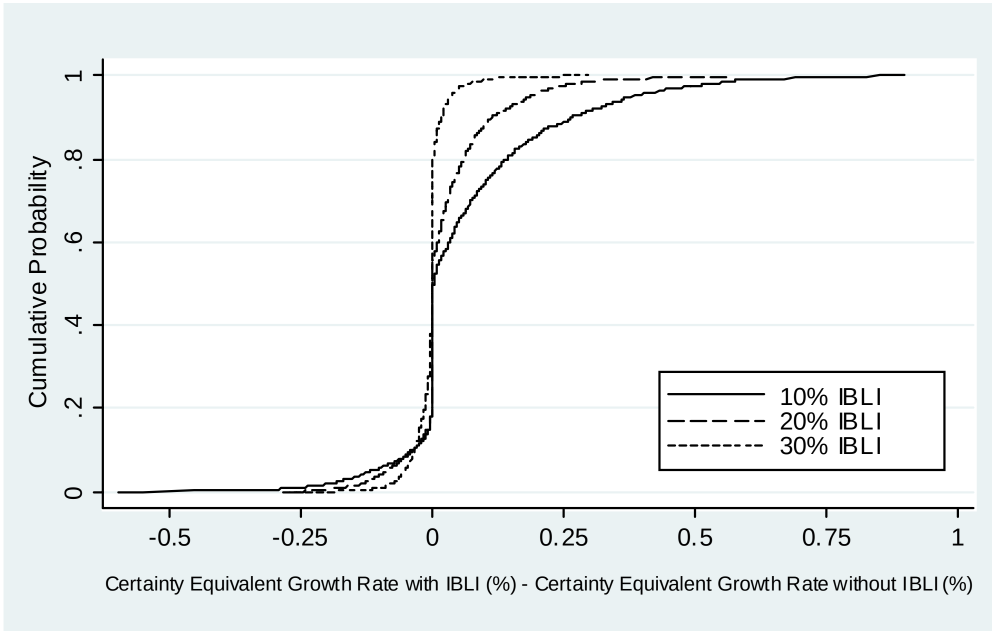

Figure 5.7 Cumulative Distributions of Change in Certainty Equivalent Growth Rate

5.7 Willingness to Pay and Potential Demand for IBLI

So far, we have explored the performance of IBLI contracts sold at actuarially fair premium rates. As premium rates change to reflect commercial loading, impacts of IBLI on herd dynamics will also likely change. How will valuation of IBLI contracts vary by the insurance price? And how will demand sensitivity to changing prices vary across different groups of pastoralists? In this section, we explore these issues for the 10% strike contract shown to have the greatest potential for pilot sales.

We first estimate the maximum willingness to pay for IBLI of each simulated pastoralist by searching for the maximum premium loading (a) according to (5.2) that still yields a positive risk premium growth rate associated with IBLI. The expected maximum willingness to pay conditional on household's beginning herd size is then estimated nonparametrically across 2000 simulated pastoralists and shown in Figure 5.8.

As shown in Figure 5.8, maximum willingness to pay for IBLI above the fair rate is only attained at a herd size of at least 15 TLU – just around the bifurcated herd threshold. Since most households' herds are below the threshold level, this implies very limited potential demand for even actuarial fair priced IBLI. The expected willingness to pay increases at an increasing rate for the those with herd sizes between 15-20 TLU and then continues to increase toward its peaks at an average of around 18% loading at the herd sizes around 40 TLU – just below the high-level herd size equilibrium – before it decreases again for the higher herd sizes. The expected maximum willingness to pay may not be high enough for a commercially viable IBLI

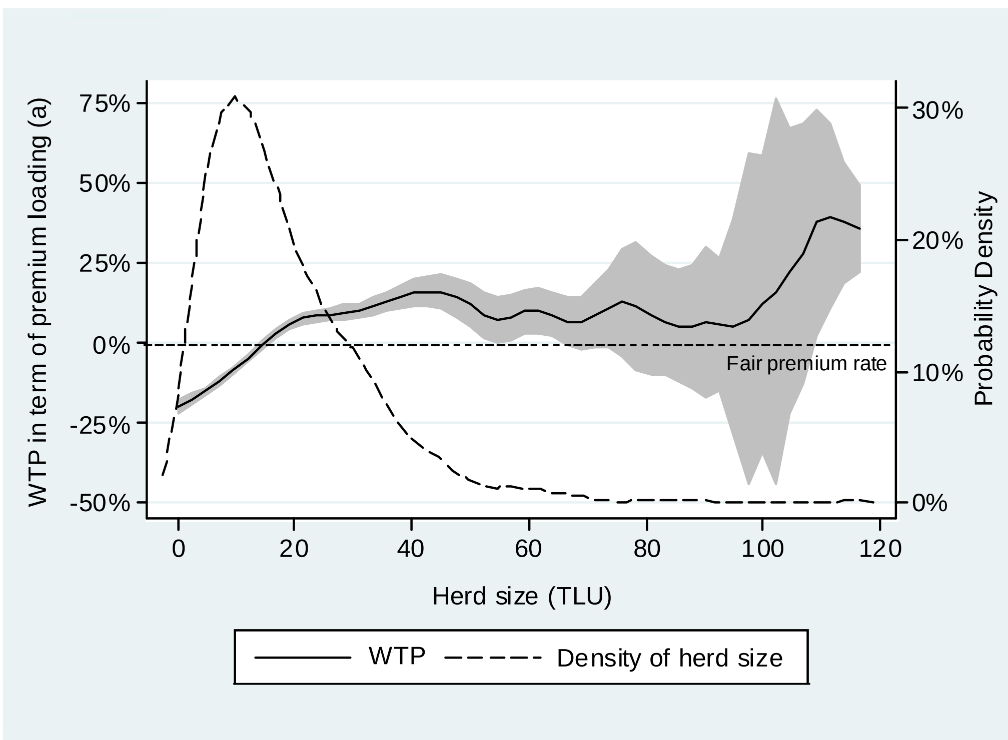

Figure 5.8 Willingness to Pay for One-Season IBLI by Beginning Herd Size

contract, which may require at least 20-30% premium loading. However, the willingness to pay of at least 30% premium loading emerges only among the smallest group of pastoralists, those with at least 100 TLU.

Based on the estimated distributions of households' maximum willingness to pay for IBLI in each location, we now study potential aggregate demand. Specifically, we proceed to construct a district-level aggregate demand curve for Marsabit district as follows. With a working assumption that the 2000 simulated households in 4 locations are randomly drawn from the total population of 27,780 households in 28 locations in Marsabit district of northern Kenya (Administrative Census of Marsabit district (1999) produced by Kenya National Bureau of Statistics and International Livestock Research Institute), we first scale up the existing simulations to reflect the district population by allowing each simulated household to represent approximately 14 households in the population. We then rank the estimated maximum willingness to pay across all population and plot premium loadings (*a*) against the cumulative number of beginning herd sizes of the population, whose maximum willingness to pay exceeds each and every loading level.

Figure 5.9 thus first presents the constructed aggregate demand for Marsabit district and disaggregates it for each of the three threshold-based herd groups: (i) the low herd group (with less than 10 TLU herd) – 26% of population occupying 7% of overall district herds – who deemed to be on a de-cumulating trajectory, (ii) vulnerable pastoralists (with between 10-30 TLU herd) – 47% of population occupying 38% of aggregate herds – who teeters on the edge of the critical herd threshold and (iii) the better off pastoralists (with greater than 30 TLU herd) – 27% of population occupying the majority of district herd, who, in the absence of a major shock, should be securely on a growth path.

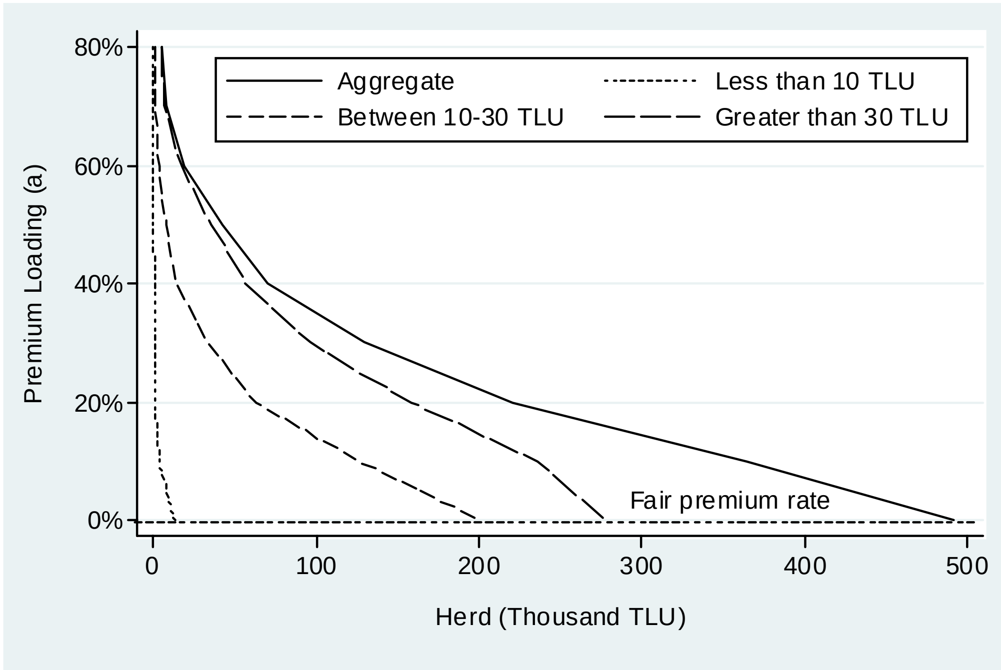

Figure 5.9 District-level Aggregate Demand for One-Season IBLI

Overall, the district-level aggregate demand for IBLI seems very price elastic with reduction in quantity demanded by 55% as the fair premium rate is loaded by 20%, and a further 26% reduction with an additional 20% premium loading. If the commercially viable IBLI contract rate is set at 20% loading, these highly elastic aggregate demand patterns show potential aggregate demand of approximately 210 thousand TLU in Marsabit District. These observed patterns of potential demand highlight several points. First, large herd owners will be the key drivers of a commercially sustainable IBLI product. Second, the observed price elasticity of demand in these locations could also imply that a small premium reduction (e.g., through subsidization) can potentially induce large increases in quantity demanded. As Figure 5.9 shows, a decrease in premium loading from 40% to 20% could potentially induce more than a doubling of aggregate demand.

Third, while IBLI is valuable for the most vulnerable pastoralists (e.g., with herd sizes around 10-30 TLU) as it could preserve their herd dynamics from catastrophic shock, the maximum willingness to pay of majority of them are still below the commercially loaded IBLI premium (e.g., of at least 20% loading). This, as we show earlier in panel (c) of Figure 5.6, is due to the possibility that high premium payment could impede herd accumulation toward growth trajectory. Consequently to preserve the growth-preserving benefit from IBLI among such vulnerable populations, premium subsidization may be critical. This point thus provides a natural link to one potentially important application of IBLI in northern Kenya as subsidizing insurance premiums for target pastoralists may serve as a cost-effective and productive safety net in broader social protection programs sponsored by governments or donors.

5.8 Enhancing Productive Safety Net Using IBLI

To explore how effective IBLI may be as a productive safety net for pastoralists in northern Kenya, we first explore herd and poverty dynamic outcomes (with asset poverty line of 10 TLU) of these 2000 simulated pastoralists in the four locations under the scenarios (i) without insurance, (ii) with commercially loaded IBLI (assuming 20% premium loading that can be met at least by the majority of large-scaled pastoralists), (iii) with the optimal targeted premium subsidization scheme that maximizes asset poverty reduction outcomes and (iv) with comparable need-based subsidization targeted to the poorest and most vulnerable (with herd size less than 20 TLU).

The targeted premium subsidization scheme is optimized by searching for the combination of subsidized premium rates targeted to different herd groups – (a) the poorest (with herd sizes less than 10 TLU), (b) the non-poor deemed to fall into poverty in long run (10-20 TLU), (c) the vulnerable non poor (20-30 TLU), (d) the moderate-scaled pastoralists (30-50 TLU) and (e) the large-scaled pastoralists with great than 50 TLU herd sizes – that yields the lowest poverty outcomes. Results imply that the optimal subsidized premium rates are at the free provision for group (b) and fair premium rate for the vulnerable non-poor groups (c) and (d), while premium subsidization to the poorest and obviously to the large-scaled groups do not change poverty outcomes so no subsidization to (a) and (e).

We then compare this with two need-based subsidization schemes: subsidized to the fair rate $(a = 0\%)$ and free provision targeted to the less well off pastoralists with herd sizes less than 20 TLU. At the asset poverty line at 10 TLU, the targeted pastoralists for subsidized IBLI thus include both the initial poor and non poor, who are deemed to fall into poverty according to the threshold-based livestock dynamics.

In each of these scenarios, individual herd at the end of each season reflects the herd associated with household's insurance choice – e.g., insure if maximum willingness to pay exceeds the premium rate or do not insure otherwise. Therefore, the herd outcomes for the case of commercial IBLI, for example, represent the outcomes of the insured herds among the majority of the well off pastoralists with potential demand and the uninsured herd of the rest of the population. Similarly, the outcomes for the case of targeted subsidizing IBLI at various rates thus represent the outcomes of the insured herd of the well off with potential demand at the non-subsidized rate and of the targeted pastoralists with induced demand at subsidized rate, and again the uninsured herd of the rest. Figure 5.10 depicts these herd dynamic outcomes in the form of mean household herd size and asset poverty headcount with respect to asset poverty line of 10 TLU constructed across 2000 simulated household over the 54 seasons of available NDVI data from the long rain – long dry season of 1982 to that of 2008.

The commercially loaded IBLI without subsidization, which can only attract the majority of the well-off pastoralists whose probability of falling into poverty is low, has a very limited role in poverty reduction. Average herd sizes under this scenario are shown to track the no-insurance case with modest increases largely among insured, well-off pastoralists whom were partially protected from shocks by IBLI. Under the optimal scheme, we observe increasing mean herd dynamics at an increasing rate with averaged increases of 10 TLU per season and the maximum increases reach 20 TLU in 2008. Poverty headcount dynamics also decreases slightly overtime and stabilize at about 10% lower than the case without insurance at the end of 2008. Such observations reflect the fact that induced demanded due to subsidized IBLI serves to preserve some targeted pastoralists' position on the growth trajectory from drought-related shocks that may otherwise collapse them into a de-cumulating path toward destitution.

This is in contrast to the need-based schemes, which achieve less than half of these optimal outcomes. Nonetheless, herd (and poverty) outcomes under the need-based subsidizing programs still follow similar trends as that under no subsidization with modest increases (decreases) as subsidization increases toward free provision. We still observe increasing poverty headcounts (though with less magnitudes) even in the free provision of IBLI. These imply that, first since IBLI contract does not perfectly provide compensation for livestock losses due to shock, the induced demanded (even the freely provided) IBLI may not be able to provide an adequate buffer to shock for some targeted pastoralists with low herd sizes or with some inherent basis risk characteristics. And second, there are still some better-off (non-targeted) but, to some extent, vulnerable pastoralists, who do not have potential demand for unsubsidized IBLI but could collapses into poverty in the occurrence of major asset shocks occurred mainly during 1984-1986, the early 1990s and 2005-06 in this region. And since herd and poverty outcomes will not change by subsidizing the poorest, whose herd sizes are far beneath the critical threshold, allocating more resources to expand premium subsidization to those not too far above the critical threshold could improve poverty reduction outcomes according to the optimal scheme.

The total cost of the optimal targeted subsidization scheme, which reaches 20%-50% of the population over 54 historical seasons, stands at an average of $50 per beneficiary per six-month season.[72] By shifting the full IBLI provision to the poorest with less than 10 TLU to the partial subsidization at the fair rate to the vulnerable non poor, this optimal scheme is thus relatively cheaper than the need-based scheme that reaches the range of 20-70% of population over the historical seasons at an average cost of $70.25 per beneficiary per season. Moreover, using percentage of poverty reduction relative to the case without subsidization, per capital cost per one percent reduction of poverty is therefore a lot cheaper for the optimal scheme at $20 per capita per 1% poverty reduction, in contrast to $38 for the need-based scheme.

This illustration supports the idea that targeting subsidized IBLI to the vulnerable non poor thus could, to some extent, provide productive safety net in the sense that it can protect some targeted populations from unnecessarily slipping into a poverty trap that they may find hard to escape (Barrett et al. 2008). Therefore, safety net in the form of subsidizing IBLI – properly targeted based on easily observed characteristics such as herd size – can prove appropriate as a cost effective poverty reduction program.

[72] One TLU is valued at 12,000 Ksh, approximately $150 based on November 2008 exchange rates (79.2 Ksh/US$).

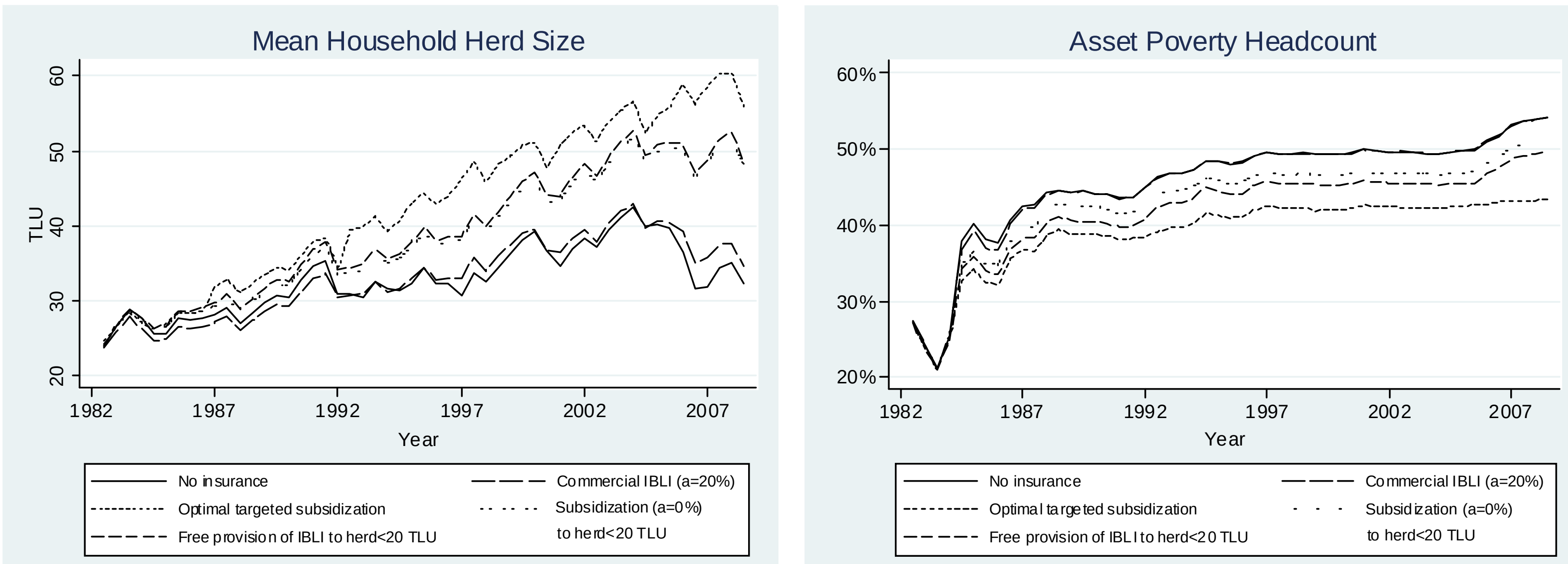

Figure 5.10 Dynamic Outcomes of Targeted IBLI Subsidization

5.9 Conclusions

Covariate livestock mortality is a key source of vulnerability among pastoralists in northern Kenya and can often drives households into extreme poverty, making it difficult for them to escape once they are destitute. Effectively managing risk should help alter these dynamics. Index based livestock insurance is designed in Chantarat et al. (2009a) as a commercially viable risk management instrument offers the promise of protecting pastoralists from the impacts of covariate herd losses and is scheduled for pilot sale in early 2010 in northern Kenya. This paper uses household-level panel data sets collected in targeted communities to provide a complete analysis of the effectiveness of IBLI in managing livestock mortality risk and improving herd and welfare dynamics of the vulnerable populations. Results and implications from this paper could provide useful information for finalizing the pilot plan.

Our analysis adds to the current literature because of our focus on asset risks – rather than income risk commonly considered – and the pastoral production system of northern Kenya characterized by the existence of bifurcation in herd accumulation, both of which combine to require a unique application of analytical tools. A dynamic model is therefore used as a basis for a suite of simulation exercises along with a modified expected utility based evaluation criterion in order to take into account the potential dynamic impact of IBLI. We use household-level variables, including household-specific risk preferences elicited from field experiment in the target areas to provide provides critical information regarding the variations and distributions of IBLI performance across households and locations needed to generate realistic simulations and explore variations in willingness to pay and aggregate demand for IBLI.

Our model and simulations show that performance of a particular IBLI contract varies greatly across households and locations with different natures of livestock asset exposures and basis-risk factors, which determines the extent to which IBLI can provide compensations for household's livestock losses. More strikingly, we show that IBLI's performance is also significantly influenced by household's herd size relative to the critical herd threshold, which potentially determines the significance of IBLI in altering herd growth dynamics under the presence of bifurcations in herd accumulation. IBLI is shown to be most valuable where it helps stem collapses into poverty of vulnerable but non-poor pastoralists following a drought shock.

In contrast to available theoretical and empirical evidence of high risk premia among the poor (Rosenzweg and Binswanger 1993, Morduch 1995, Dercon 1996, among others), IBLI performance is shown to be minimal among pastoralists with very small herds far below the critical threshold despite our elicited risk preference that also exhibits the widely evidenced inverse relationship between risk preference and wealth. In our model, IBLI is not well suited for the poorest, who already slowly collapse toward destitution over time, as the premium payment tends to further speed up such herd de-cumulation during good seasons.

This implication, however, holds true in our setting as we abstract away from other potential behavioral responses to IBLI that may lead to improved welfare outcomes. The extent to which the poor can reduce their costly risk management strategies may lead to slightly different outcomes. We also ignore the possibility that IBLI can crowd-in much needed credit for the insured pastoralists including the least well-off ones in order for them to expand their herd to achieve high-growth trajectory over time. With such possibility, the value of IBLI should be more significant.

The joint impact of ex ante herd sizes and household-specific basis-risk determinants thus results in location-averaged performances that can be ranked positively with mean beginning herd size and negatively with dispersion of unpredicted asset risk. IBLI Performance is high in the main pastoral locations of

North Horr and Kargi relative to Dirib Gombo with the lowest performance of IBLI due to smallest proportion of large-scaled pastoralists and the largest dispersion of uncovered livestock asset risk. This result holds despite the evidence that predicted mortality index, on average, over-predicts the actual location-averaged mortality losses in North Horr relative to others. Therefore, our results imply that though the out-of-sample forecasting performance of the predicted mortality index serves to determine effectiveness of IBLI, the variations and distribution of beginning herd sizes and other household-specific factors seem to play a larger role in determining overall performance of IBLI in each particular area. As such, studies that ignore household-level variations may fall short of accurately capturing the performance of similar insurance contracts.

Our result shows that 10% strike contract with the highest coverage of covariate risk out-performs others for each household and location, and is there chosen for the optimal contract used in the ensuing simulations. The district-level aggregated demand is shown to be high price elastic with evidence of potentially low demand for commercially viable contract. Willingness to pay among the most vulnerable pastoralists is very sensitive to premium loadings and lower than the commercially viable rates, on average, despite its potentially high dynamic value. We therefore illustrate that safety nets in the form of subsidizing IBLI, properly targeted based on easily observed characteristics such as herd size, can prove appropriate as a cost effective poverty reduction program. Our future empirical research to be implemented in parallel to the pilot sale of IBLI early next year will provide greater insight for the most effective way to implement IBLI as a productive safety net in northern Kenya.

APPENDIX A

APPENDIX TO CHAPTER 4

A.1 Descriptive Statistics of Vegetation Index and Livestock Mortality

Table A.1 Descriptive Statistics for Vegetation Index Regressors and Area-Average Seasonal Mortality, by Location and Regime (2000-2008)

Cluster/ Location	Variable	Overall				Good Year Czndvi_pos>=0		Bad Year Czndvi_pos<0		% Bad-Climate Regime
		Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	
Chalbi (Pooled)	Mortality rate	0.1	0.2	0.0	0.7	0.0	0.1	0.1	0.2	60%
	Czndvi_pos	-1.5	15.9	-26.3	25.9	15.8	7.4	-12.9	7.3	
	Czndvi_pre	-0.7	9.9	-19.6	21.8	8.6	7.4	-6.8	5.7	
	CNzndvi	6.4	4.6	0.1	18.6	2.5	1.6	8.9	4.1	
	CPzndvi	5.5	6.0	0.0	21.4	9.9	7.0	2.6	2.7	
North Horr	Mortality rate	0.1	0.2	0.0	0.6	0.0	0.0	0.2	0.2	56%
	Czndvi_pos	-4.8	14.3	-26.2	17.4	9.0	5.7	-15.5	7.9	
	Czndvi_pre	-2.5	9.5	-19.6	18.3	5.0	6.7	-8.4	7.0	
	CNzndvi	6.9	5.0	1.6	18.6	3.3	1.3	9.7	5.1	
	CPzndvi	4.4	5.3	0.0	20.7	7.3	6.6	2.2	2.7	
Kalacha	Mortality rate	0.1	0.2	0.0	0.7	0.0	0.0	0.2	0.2	63%
	Czndvi_pos	-1.5	17.9	-26.3	25.9	19.3	5.9	-14.0	7.4	
	Czndvi_pre	-0.6	10.9	-16.5	21.8	10.2	8.4	-7.1	5.9	
	CNzndvi	6.6	5.0	0.6	16.3	2.1	1.5	9.4	4.2	
	CPzndvi	5.6	6.7	0.0	21.4	11.3	7.9	2.2	2.4	
Maikona	Mortality rate	0.1	0.1	0.0	0.4	0.1	0.1	0.1	0.1	63%
	Czndvi_pos	1.8	15.7	-17.4	24.4	20.3	4.5	-9.3	5.8	
	Czndvi_pre	1.0	9.5	-10.8	18.7	11.2	6.7	-5.1	4.0	
	CNzndvi	5.6	4.0	0.1	11.1	1.9	2.0	7.8	3.1	
	CPzndvi	6.3	6.1	0.0	19.9	11.4	6.8	3.3	3.0	
Laisamis (Pooled)	Mortality rate	0.1	0.1	0.0	0.6	0.0	0.0	0.1	0.2	59%
	Czndvi_pos	-3.5	16.5	-35.3	34.9	12.9	9.0	-14.7	9.7	
	Czndvi_pre	-1.9	10.1	-20.3	23.0	6.0	7.9	-7.4	7.7	
	CNzndvi	6.7	5.1	0.0	19.6	2.5	2.1	9.6	4.6	
	CPzndvi	4.8	5.8	0.0	24.1	9.3	5.7	1.8	3.6	

Continued on next page…

…Table A.1 (continued)

Cluster/ Location	Variable	Overall				Good Year Czndvi_pos>=0		Bad Year Czndvi_pos<0		% Bad-Climate Regime
		Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	
Karare	Mortality rate	0.1	0.2	0.0	0.6	0.1	0.0	0.2	0.2	63%
	Czndvi_pos	-5.8	12.7	-26.8	19.1	7.3	7.4	-13.6	7.5	
	Czndvi_pre	-3.1	7.8	-16.0	12.3	2.5	6.2	-6.4	6.9	
	CNzndvi	6.5	4.4	0.3	16.3	2.4	1.2	8.9	3.8	
	CPzndvi	3.4	3.7	0.0	13.4	6.8	4.1	1.3	1.2	
Logologo	Mortality rate	0.1	0.1	0.0	0.4	0.0	0.0	0.1	0.2	50%
	Czndvi_pos	-2.5	17.4	-26.3	26.5	13.1	7.5	-18.1	5.6	
	Czndvi_pre	-1.4	10.5	-14.9	17.2	6.1	8.7	-8.9	5.7	
	CNzndvi	6.2	4.9	0.2	14.6	2.3	1.4	10.1	3.9	
	CPzndvi	4.8	6.3	0.0	18.7	9.3	6.3	0.4	0.5	
Ngurunit	Mortality rate	0.1	0.1	0.0	0.4	0.0	0.0	0.1	0.1	63%
	Czndvi_pos	-4.3	16.8	-35.3	22.8	11.8	7.7	-14.0	12.6	
	Czndvi_pre	-2.3	10.2	-20.3	16.1	5.4	6.2	-7.0	9.5	
	CNzndvi	7.0	6.0	0.2	19.6	2.5	2.5	9.7	5.8	
	CPzndvi	4.6	5.0	0.0	17.1	8.7	4.6	2.2	3.6	
Korr	Mortality rate	0.1	0.1	0.0	0.4	0.0	0.0	0.2	0.2	63%
	Czndvi_pos	-1.4	19.8	-30.1	34.9	19.2	11.4	-13.7	11.4	
	Czndvi_pre	-1.0	12.3	-17.7	23.0	9.9	9.5	-7.5	8.8	
	CNzndvi	7.2	5.5	0.0	17.2	2.9	3.4	9.8	4.9	
	CPzndvi	6.5	7.7	0.0	24.1	12.2	7.0	3.0	6.0	

A.2 Estimated Annual Loss Ratios

Table A.2 Estimated Annual Loss Ratios under Pure Premia, 1982-2008

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

A.3 Annual Premia, Indemnities and Reinsurance

Table A.3 Annual Unconditional Premia, Indemnities and Reinsurance for Hypothetical IBLI Contracts at 10% Strike (1982-2008)

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

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

APPENDIX B

APPENDIX TO CHAPTER 5

B.1 Non-mortality Component of Herd Growth Function

Chantarat at al. (2009a) defines good seasons as those with positive cumulative deviation of NDVI observed at the end of the season. The two nonparametrically estimated non-mortality component of growth functions conditional on vegetation conditions, which will be used as the basis for the simulations, are plotted below. The conditional herd mortality rates are also plotted here to illustrate that during the good seasons, more households can enjoy positive net growth rates, while those above the bifurcated threshold maintains just slightly above zero growth during the bad seasons. Similar finding appeared in Santos and Barrett (2007).

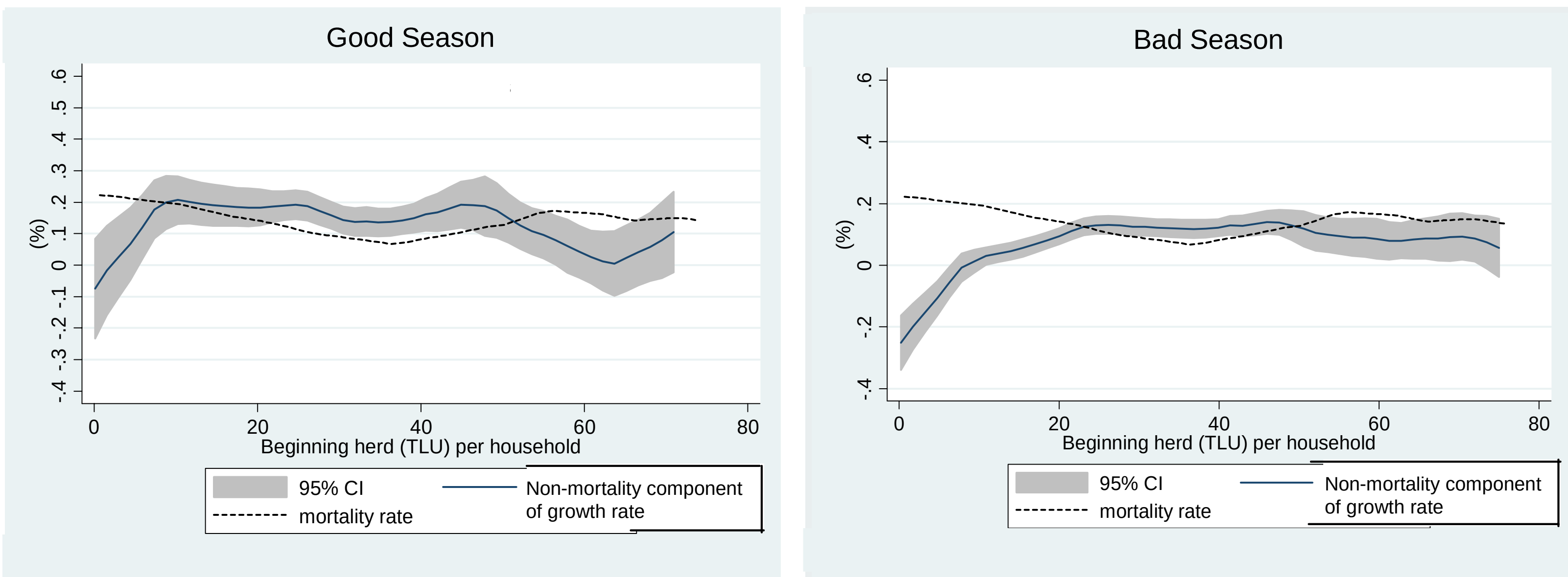

Figure B.1 Non-mortality Component of Herd Growth Function, 2000-02, 2007-08

B.2 Summary of Estimated and Simulated Household Characteristics

Table B.2 Summary of Estimated and Simulated Household Characteristics

Regression of individual mortality on predicted mortality index*

Location	Variable (Best-fit distn)	Obs.	Estimated		Simulated	
			Mean	S.D.	Mean	S.D.
Household-specific βi						
Dirib	ExtValue(0.7,0.6)	20	1.08	0.66	1.05	0.60
Kargi	Logistic(0.7,0.2)	25	0.71	0.39	0.70	0.34
Logologo	Normal(1.1,0.4)	27	1.13	0.38	1.13	0.38
North Horr	Logistic(0.3,0.1)	22	0.37	0.18	0.36	0.16

Variable	Estimated		Simulated	
	Mean	S.D.	Mean	S.D.
Household-specific non-drought related loss ε_{ilt} (%)				
(Based on the model estimations)	-0.02	0.20	-0.01	0.18
	0.00	0.08	0.00	0.08
	0.00	0.11	0.00	0.13
	0.00	0.08	0.00	0.07

Regression of predicted residual on location averaged residual**

Location	Variable (Best-fit distn)	Obs.	Estimated		Simulated	
			Mean	S.D.	Mean	S.D.
Household-specific $\beta_{\varepsilon i}$						
Dirib	ExtValue(0.6,0.7)	20	1.01	0.77	1.02	0.80
Kargi	Normal(1,0.3)	25	1.00	0.27	1.01	0.26
Logologo	Logistic(1,0.1)	27	1.00	0.26	1.00	0.26
North Horr	ExtValue(0.9,0.2)	22	1.01	0.32	1.00	0.29

Variable (Best-fit distn)	Estimated		Simulated	
	Mean	S.D.	Mean	S.D.
Idiosyncratic loss e_{ilt} (%)				
LogLogistic(-1,1,17.7)	0.00	0.12	0.00	0.14
LogLogistic(-0.3,0.3,6.9)	0.00	0.07	0.00	0.06
LogLogistic(-1.4,1.4,27.1)	0.00	0.10	0.00	0.11
Lognorm(0.4,0.04,RiskShift(-0.4))	0.00	0.04	0.00	0.04

Note: * Estimated using pooled data, n = 93×4 = 372, log likelihood = 167.5. ** Estimated using pooled data, n = 93×4 = 372, log likelihood = 303.17.

Continued on next page…

…Table B.2 (continued)

Other key household characteristics

Location	Variable (Best-fit distn)	Obs.	Estimated Mean	Estimated S.D.	Simulated Mean	Simulated S.D.
Household-specific long-term mean mortality rate μ_{il} (%)						
Dirib	Logistic(0.2,0.1)	20	0.22	0.14	0.23	0.11
Kargi	Logistic(0.1,0.02)	25	0.11	0.05	0.11	0.05
Logologo	Logistic(0.1,0.04)	27	0.15	0.07	0.15	0.06
North Horr	Logistic(0.06,0.03)	22	0.07	0.05	0.07	0.05

Variable (Best-fit distn)	Estimated Mean	Estimated S.D.	Simulated Mean	Simulated S.D.
Houehold's beginning herd size H_{ilt} (TLU)				
Lognorm(30.2,9.6,RiskShift(-15.3)	12	10	12	8
InvGauss(37.5,60.8,RiskShift(-4.3)	33	31	34	29
InvGauss(19.8,33.7,RiskShift(-2))	18	15	17	14
Normal(29.6,15.1)	26	17	30	15

B.3 Summary of Baseline Simulation Results

Table B.3 Summary of Baseline Simulation Results

Household-specific mortality rate (%) M_{ilt}

Location	Observed in PARIMA (2000-2002)				Simulated (1982-2008)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Dirib	0.21	0.29	0.00	1.00	0.19	0.20	0.00	1.00
Kargi	0.11	0.12	0.00	0.50	0.11	0.10	0.00	0.95
Logologo	0.15	0.19	0.00	0.74	0.14	0.15	0.00	1.00
North Horr	0.07	0.10	0.00	0.37	0.07	0.08	0.00	0.54

Household-specific growth rate in (%) g_{ilt}

Location	Estimated (2000-2002, 2007-2008)				Simulated (1982-2008)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Dirib	-0.05	0.12	-0.22	0.14	-0.07	0.14	-0.84	0.38
Kargi	0.05	0.07	-0.22	0.22	0.04	0.12	-0.23	0.38
Logologo	0.02	0.10	-0.22	0.30	0.01	0.14	-0.23	0.38
North Horr	0.07	0.11	-0.22	0.22	0.08	0.07	-0.23	0.38

Household-specific herd size H_{ils}

Location	Observed (2000-2002, 2007-2008)				Simulated			
					Beginning		1982-2008	
	Mean	S.D.	Min	Max	Mean	S.D.	Mean	Sd
Dirib	5	8	0	30	6	10	6	16
Kargi	21	39	0	224	20	43	43	38
Logologo	15	17	1	64	16	21	14	23
North Horr	24	32	0	53	24	33	68	37

B.4 Summary of Risk Preference Elicitation

The left panel of Table B.4 presents the gambling choice set with 50% probability of yielding either a low or high payoff. The first gamble choice reflects the situation if the pastoralist chooses instead not to play the game and so to keep 100 Ksh compensation. For gamble choice 2-5, expected return[73] increases by 5 Ksh and also the risk (standard deviation) increase by 25. Gamble choice 6, however, involves only an increase in risk with the same expected return as gamble choice 5. Extreme risk averse pastoralists would sacrifice expected return to avoid risk and choose the sure bet (Gamble 1). A moderate risk averse household would choose an intermediate bet (Gamble 2-4). Risk neutral pastoralist would choose gamble choice 5-6, which have the highest expected return. And the risk seeker would choose gamble choice 6 to speculate for the higher payoff. This experiment was designed to be as simple as possible, while retaining reasonable ranges of risk choices.

Though this simple elicitation method produces, seemingly coarser, six categorization of degree of risk aversion, risk decisions are expected to be substantially less noisy while maintaining equal predictive accuracy comparing to other complicated methods, especially among the low literate subjects (Dave et al. 2007; Dohmen et al. 2007; Anderson and Mellor 2008, among others). These studies found that different cognitive ability was found to hamper subject's ability to reveal their true preference. Moreover, our experimental setting that required subjects to use their earned money to play for real monetary payoff is expected to further encourage the extraction of household's true preference comparing to other hypothetical

[73] For gamble 2-5, the sample numbers are linearly related to the properties of the gamble in term of expected return and variance. The relationship between expected return and variance can be summarized by $E(R) = 100 + 0.2SD$. The gamble number (G) can be written as $G = 0.2E(R) - 19$. The gamble number is therefore a reasonable parametric summary index of risk preference.

methods) Kahneman and Tversky 1979; Holts and Laury 2002; Anderson and Mellor 2008).[74]

We estimate the range of coefficients of relative risk aversion implied by each possible choice of gambles under the assumption of constant relative risk aversion (CRRA) according to:

$$E(U(P)) = \sum_k \pi_k U(P_k) = \sum_k \pi_k \left(\frac{P_k^{1-r}}{1-r} \right) \quad , U'(P) > 0,\ \ 0 \le \pi \le 1 \text{ and } k\text{=1,2.}$$

π represents probability of each possible payoff P and r is the CRRA coefficient. In each case, the upper (lower) bound of *r* can be calculated as the value of *r* that generates same utility level for the payoffs associated with the preferred gamble and the less (more) risky adjacent. The value of *r* between 0 to 1 represents the level of preference of risk averse household.[75] The $r = 0$ is associated with the risk neutral household and r<0 is for the risk seeker. Following Binswanger (1980), we assign a mean CRRA measures to each of the ranges using the geometric mean of the two end points.[76] In the case of gamble 6, a value of zero is given to the CRRA measure to represent a class of risk neutral or risk seeker. The value of one is then assigned to the case of gamble 1 to represent the extremely risk averse class. Six risk aversion classifications (extreme, severe, intermediate, moderate, low/neutral and neutral/risk seeker), slightly similar to Binswanger (1980), are further assigned to each of the case.

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[74] There are, of course, some tradeoff benefits of the hypothetical experiment setting that better reflects pastoralist's real risk decision making – e.g., about pastoral choice – which seems to lead the subject to critically think and response in a way that reflects how they would behave un actual situations of choices. Nevertheless, the potential costs for these hypothetical surveys are found to be very unstable and subjected to serious interview bias (Binswanger 1980, among others). We think that these costs outweigh the potential benefits.

[75] In our setting, we truncated r at the maximum value of 1 as we only consider CRRA class utility function that is increasing. Value of r greater than 1 will yield negative value of utility.

[76] For the case of gamble 5 with one of the end point at zero, arithmetic mean was chosen in this case.

Table B.4 Summary of Setting of Risk Preference Elicitation

Gamble Choice	High Payoff	Low Payoff	Expected Payoff	S.D. Payoff	CRRA ranges	Geometric mean CRRA	Risk aversion class
1	100	100	100	0	r>0.99*	1.0	Extreme
2	130	80	105	25	0.55<r<0.99*	0.7	Severe
3	160	60	110	50	0.32<r<0.55	0.4	Intermediate
4	190	40	115	75	0.21<r<0.32	0.3	Moderate
5	220	20	120	100	0<r<0.21	0.1	Low/Neutral
6	240	0	120	120	r<0	0.0	Neutral/risk seeking

Note: *Without assumption of $r \leq 1$, the actual value of r is 1.67.

Figure B.4 plots cumulative distributions of CRRA associated with each of the three livestock wealth groups defined based on the local standards used in the survey sample stratification.

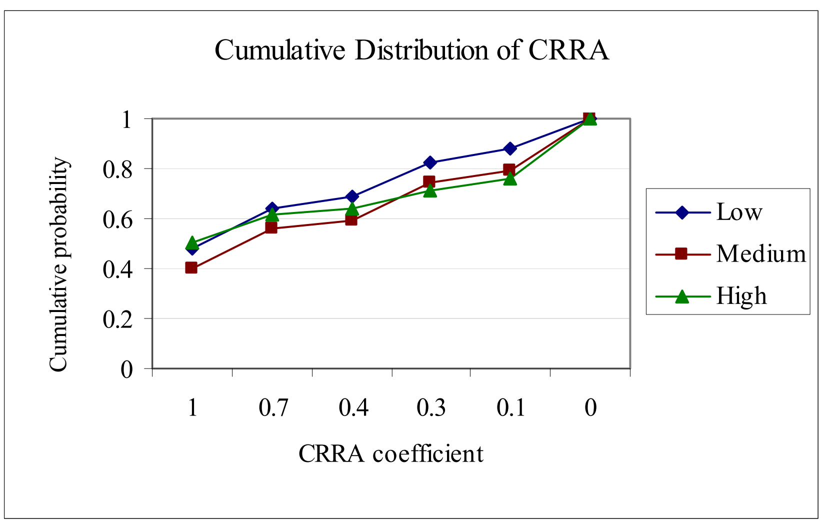

Figure B.4 Cumulative Probably Distribution of CRRA by Livestock Wealth Class

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