Dynamic Effects of Index Based Livestock Insurance on Household Intertemporal Behavior and Welfare\(^1\)

Munenobu Ikegami\(^2\) and Christopher B. Barrett\(^3\)

January 23, 2011

**Abstract**

We quantify the effects of Index Based Livestock Insurance in Marsabit, Kenya on household behavior and welfare. Index-based insurance attracts attention as a potentially effective tool for reducing vulnerability of agricultural households in developing countries. However, the literature has not studied how much household intertemporal behavior and welfare would change by reduced production risk and shock due to index-based insurance. We fill this gap in the literature by fitting household asset accumulation model to pastoralists in Marsabit, Kenya and implementing counter-factual policy simulations in order to quantify the effects of Index Based Livestock Insurance.

*Keywords*: index-based agricultural insurance, livestock, drought risk, pastoralists, Kenya

*JEL classification*: D9, O12, Q12

---


\(^2\) International Livestock Research Institute, Old Naivasha Road, P.O. Box 30709, Nairobi 00100 Kenya. Email: m.ikegami@cgiar.org

\(^3\) Charles H. Dyson School of Applied Economics and Management, 315 Warren Hall, Cornell University, Ithaca, NY 14853-7801 USA. Email: cbb2@cornell.edu
1 Introduction

Index-based insurance attracts attention from development agencies as a tool for reducing the vulnerability of agricultural households and increasing their resilience and welfare (Barnett, Barrett and Skees 2008, Barnett and Mahul 2007). In attempting to quantify the insured’s behavioral effects of index-based agricultural insurance, previous studies fail to take into account households’ intertemporal decisions such as asset accumulation. The focus to date has been on the possibility that index-based insurance reduces risk averse households’ income fluctuations by partially offsetting poor realizations of agricultural income, thereby increasing welfare. But there can be further positive effects of index-based insurance in addition to this direct effect. Since the household faces reduced risk in agricultural production, it should reduce its precautionary saving – such as grain storage or cash under mattress – or crowd in credit access – need citations - and invest more in productive agricultural assets and thereby increase productivity and income. Induced behavioral effects could lead to general equilibrium effects, for example, increased ?? could affect equilibrium input and rangeland output ?? ?? ?? ?? livestock insurance ???. The induced change in stoking rates could affect the supporting rangeland ecosystem. These induced behavioral effects have thus far been ignored in the literature.

In this paper, we model the effects of index-based insurance on household behavior and welfare, including not only the direct welfare effects of reduced income risk but also the indirect effects of induced household responses to reduced risk and reduced negative net income shocks by applying a dynamic household investment model to data from pastoralists in Northern Kenya. These pastoralists face drought and associated risks that are large in magnitude (frequently causing a 20-40% livestock mortality rate) and frequent (once every 4-5 years). The International Livestock Research Institute (ILRI) and its research and implementation partners launched a commercial Index Based Livestock Insurance (IBLI) product in January 2010 in an effort to mitigate the negative consequences of livestock mortality risk (Chantarat et al. 2009a, 2009b; see also the IBLI project web site: http://www.ilri.org/ibli). It will take a long time, however, to obtain empirical results from the ex post impact evaluation based on several years’ household panel data. This paper, instead, offers an ex ante impact evaluation based on a dynamic household investment model calibrated with household data from the region.

A key feature of the model is that livestock is not only a productive asset, it is also the prime form in which pastoralist households’ engage in precautionary savings. If the former aspect of livestock dominates the latter, IBLI should induce pastoralists to increase their herd sizes as the risk of livestock loss falls, conversely, if precautionary savings effects dominate, her size may fall.

This question has important policy implications. Previous studies show that livestock density in pastoral regions often reaches levels where overgrazing deteriorates production efficiency and the natural rangeland environment (Dest a and Coppock 2002, Fafchamps 1998)4. If IBLI induces increased livestock houldings, it could bring overgrazing and

---

4 This is a contentious point in the range science literature. Other studies suggest that livestock stocking density rarely leads to rangeland carrying capacity collapse, as livestock’s boom and bust cycle is determined by water and vegetation availability rather than by livestock density (Ellis and Swift 1988, Lybbert et al. 2004,
environmental degradation. Other questions this model lets us explore include: How much of their herd and under what conditions do pastoralists insure? At present, very little is known about index-based insurance demand patterns. Perhaps, most importantly, how much would the insurance reduce pastoralists’ vulnerability, increase their resilience against herd mortality shocks, and improve their welfare in the long run? We answer these questions by calibrating the household investment model to existing household data from the region in order to get preliminary answers before we can observe the long-term consequence in the IBLI monitoring data.

The remainder of this paper is organized as follows. The next section situates this paper in the literature. Section 3 explains our methodology. Our model is developed in Section 4. Section 5 introduces the data. Section 6 explains how we fit the model to the data. Then, in section 7, we implement counter-factual simulations of IBLI and quantify the estimated effects of the insurance on household intertemporal behavior and welfare in the long term. Section 8 concludes this paper.

2 Previous Studies

Previous economic analyses show that index-based insurance is effective when asymmetric information between insurance company and the insured is large, transaction costs are high, and basis risk is small (Mahul (1999), Mahul and Wright (2003), Miranda (1991), Miranda and Glauber (1997), Vercaemmen (2000), Zant (2008)). All of these previous studies focus on short term effects of index based insurance, or estimate long term effects as just a multiplication of the effects in one time period times the number of time periods. Like this paper, Chantarat et al. (2009a) study the long term effects of Index Based Livestock Insurance. But Chantarat et al. (2009a) focus on the poverty trap structure of livestock accumulation in the region and investigate induced investment effects on which we focus, the poverty dynamics. Our model accommodates change in investment and purchase decisions when herd size changes and the existence of IBLI changes; Chantarat et al. (2009a) assume that household’s investment decision under IBLI is the same as one without IBLI and that insurance coverage decisions are the same over time at full insurance level. Previous empirical studies on pastoralists in Northern Kenya and Southern Ethiopia found poverty trap in herd accumulation (Lybbert et al. (2004), Barrett et al. (2010), Santos and Barrett (2006)). However, these results are based on reduced form estimation and previous studies do not identify structures generating poverty trap herd dynamics. Since this paper’s focus is on dynamic household decisions, we assume the economic structure without a poverty trap. We leave accommodating a poverty trap structure as a future research topic.

3. Methodology

We model household livestock investment decisions and estimate a livestock production function and the stochastic structure of livestock accumulation separately based on the Pastoral Risk Management (PARIMA) project quarterly household panel data collected in northern Kenya from July 2000 to June 2002. Note that IBLI was first sold in February 2010.
and we fit the model to data collected prior to the introduction of IBLI.

IBLI’s index is predicted livestock mortality based on the regression of livestock mortality data collected by Kenyan government’s Arid Land Resource Management Program (ALRMP) on vegetation conditions observed from satellite and reflected in the Normalized Differenced Vegetation Index (NDVI), from 1981 to 2009 provided by National Aeronautics and Space Administration (NASA) / National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) (Chantar et al. 2010b). We use PARIMA data, NDVI and the IBLI’s regression model from Chantar et al. (2010b) to recover the stochastic structure of livestock and vegetation.

We fit the model to the data in two steps. First, we estimate a milk production function and a livestock transition function separately and directly from the data. Second, we calculate optimal investment and insurance purchase decisions based on the model calibrated with the first step estimates. Based on this estimated structural model and its parameters, we introduce insurance into the model and predict and simulate uptake of the index-based livestock insurance and resulting livestock investment.

4 Model

4.1 Without index-based livestock insurance

Denote household i’s livestock measured in tropical livestock unit (TLU\(^5\)) in the beginning of season \(t\) by \(k_i\). There are two seasons: long rain and long dry (LRLD) season and short rain and short dry (SRSD) season. If \(t\) is even, the season is LRLD. Livestock accumulation follows the law of motion

\[
k_{i,t+1} = k_i + b_u k_u + p_{uit} - s_{lit} - \tilde{s}_{uit} - (\theta_u + \xi_u) k_i
\]

where \(b_u\), \(p_{uit}\), \(s_{lit}\), and \(\tilde{s}_{uit}\) are birth rate, purchases, slaughter for own consumption and sale of livestock, respectively. \(\theta_u\) and \(\xi_u\) are idiosyncratic and covariate mortality shocks, respectively. The household’s budget constraint each period is

\[
c_i + p_i p_{uit} = f + p_i (\tilde{s}_{uit} + s_{lit}) + y_{nli} \tag{2}
\]

where \(c_i\) is consumption of composite good, \(f\) is milk income, \(y_{nli}\) is time-invariant income from non-livestock production (e.g. remittances, food aid transfers, wage income), \(p_i\) is the price of 1 TLU of livestock. Household own consumption of animal products is included in \(c_i\). We assume the extreme version of credit constraints, that is, the household cannot borrow at all\(^6\). Since we assume that 1 TLU is the same price regardless of whether the household purchases or sells 1 livestock and we can simplify the livestock accumulation equation (1), the budget constraint (2) and the household’s control variables by defining net livestock investment \(\hat{i}_i = p_i - s_{uit} - s_{lit} \).

\(^5\) 1 TLU is equivalent to 1 cattle, 0.7 camel, 10 sheep, or 10 goats.

\(^6\) We can relax this assumption by allowing the household to borrow some amounts up to some limit, for example, some percentage of livestock value, without changing the qualitative findings but of the cost of added, unnecessary cluties? in the model.
Denote the Normalized Differential Vegetation Index (NDVI), a measure of rangeland forage condition, indirectly useful ??? zilzbility???, in season t by \( n_t \). We assume that only the values of NDVI in the preceding two seasons \( (n_{t-2}, n_{t-1}) \) affect the value of NDVI in the current season \( n_t \), that is,
\[
n_t \sim g_n(n_t \mid n_{t-2}, n_{t-1}) \quad (3)
\]
where \( g_n(\cdot \mid \cdot) \) is a conditional probability density function. The probability distributions of \( b_{it} \), \( \theta_{it} \), and \( \xi_i \) are assumed to be functions of \( n_t \) and \( n_{t-1} \):
\[
\begin{align*}
b_{it} &\sim g_b(b_{it} \mid n_{t-1}, n_t) \\
\theta_{it} &\sim g_{\theta}(\theta_{it} \mid n_{t-1}, n_t) \\
\xi_i &\sim g_{\xi}(\xi_i \mid n_{t-1}, n_t).
\end{align*}
\]
Since vegetation conditions \( (n_{t-1}, n_t) \) affect births \( b_{it} \), it affects milk production as well. The milk production function is defined as \( f = f(k_{it}, n_{t-1}, n_t) \). We assume that \( f(\cdot; \cdot) \) is concave and monotonically increasing in \( k_{it} \) and \( f(0, n_{t-1}, n_t) = 0 \).

The timing of events is as follows. In the beginning of season \( t \), the nature draws \( n_t \) given \( n_{t-1} \) and \( n_{t-2} \), determining the period specific birth rate \( b_{it} \) and negative mortality shocks \( (\theta_{it}, \xi_i) \). Given this realization of random variables and non-livestock income, \( y_{ali} \), household \( i \) decides investment \( i_{it} \) and consumption \( c_{it} \). The household’s livestock herd size in the beginning of the next season \( t+1 \) is determined by the livestock accumulation equation (1). The household maximizes its discounted utility:
\[
\max_{c_{it}} \beta^{-1} u(c_{it})
\]
\[
\text{s.t. } k_{it} \geq 0
\]
where \( u(c_{it}) = m_{it} \frac{(c_{it}/m_{it})^{1-\theta_u} - 1}{1-\theta_u} \), \( m_{it} \) is the number of household members and \( \theta_u \) is the risk aversion parameter. The household’s maximization problem in the middle of season \( t \) is summarized in the following Bellman equation:
\[
V_A(k_{it}, m_{it}, n_t, n_{t-1}, y_{ali}, b_{it}, \theta_{it}, \xi_i) =
\max_{c_{it}} u(c_{it}) + EV_A(V_A(k_{it+1}, m_{it+1}, n_{t+1}, n_t, y_{ali+1}, b_{it+1}, \theta_{it+1}, \xi_i))
\]
\[
\text{s.t. } c_{it} = f(k_{it}) + s_{it} + y_{ali}
\]
\[
k_{it+1} = k_{it} + b_{it} k_{it} + i_{it} + (\theta_{it} + \xi_i) k_{it}
\]
\[
given k_{it}, m_{it}, n_t, n_{t-1}, y_{ali}, b_{it}, \theta_{it}, \xi_i
\]
\[ EV_A(k_{ix+1}, m_{ix+1}, n_{ix+1}, n_i, b_{ix+1}, \theta_{ix+1}, \xi_{ix+1}) \]
\[ = \sum_{k_{ix+1}} \sum_{m_{ix+1}} \sum_{n_{ix+1}} \sum_{n_i} \sum_{b_{ix+1}} \sum_{\theta_{ix+1}} \sum_{\xi_{ix+1}} V_A(k_{ix+1}, m_{ix+1}, n_{ix+1}, n_i, b_{ix+1}, \theta_{ix+1}, \xi_{ix+1}) \]
\[ g_i(b_{ix+1}, n_i) g_{ix+1}(n_{ix+1}, b_{ix+1}, \theta_{ix+1}, \xi_{ix+1}) g_{ix+1}(n_{ix+1}, n_i) g_{ix+1}(n_i, n_{ix+1}) \]
\[ db_{ix+1} d\theta_{ix+1} d\xi_{ix+1} dn_{ix+1}. \]

Subscript \( A \) under the value function \( V \) represents autarky, distinguishing it for economic environment with the ??? ??? index-based livestock insurance. We ??? compare this value function and its resulting behavioral ??? with the one when index-based livestock insurance is available. Denote the optimal net accumulation of livestock under autarky by \( i^*_A \).

4.2 With Index Based Livestock Insurance

In this subsection, we consider the case in which an insurance company provides IBLI to a household (Chantarat et al. 2009a, b). IBLI is sold at the end of dry seasons (January-February and August-September) before households observe rain and make predictions about vegetation. IBLI is offered as an annual contract covering predicted livestock mortality risk for the following one year period with the possibility of seasonal indemnity payouts. For example, if a household buys the insurance in January-February 2010, there can be an indemnity payout for LRLD (March-September) season in October 2010 and another indemnity payout for SRSD (October-February) season in March 2011.

The IBLI contract is defined as

\[ I(\overline{m}, p_{O_{t+1}}, p_{O_{t+2}}, p_{O_{t+1}}, p_{O_{t+2}}, n_i, n_{t+1}, n_{t+2}, \hat{m}(\cdot), \hat{k}_{t+1}, \hat{k}_{t+2}) \]

where \( p_{O_{t+1}} \) and \( p_{O_{t+2}} \) are premium and indemnity payouts of the insurance, respectively, \( \hat{k}_{t+1} \) and \( \hat{k}_{t+2} \) is the amount (TLU) of household \( i \)'s livestock to be insured for season \( t+1 \) and season \( t+2 \), \( \hat{m} \) is the predicted livestock mortality index, and \( \overline{m} \) is the strike point in the index, above which the insurance company provides indemnity payouts. \( \hat{k}_{t+1} = 0 \) means the household does not buy the insurance. If the household has already bought the insurance in the previous season and insured livestock for season \( t \) and season \( t+1 \), that is, \( \hat{k}_{t+1} > 0 \), the household cannot buy the insurance at the current season and insure livestock for season \( t+1 \) and season \( t+2 \). That is, if \( \hat{k}_{t+1} > 0 \), then \( \hat{k}_{t+2} = 0 \) should holds.

Indemnity payout \( p_{Oi} \) is based on the contract \( I(\cdot) \), the insured livestock value \( \hat{k}_{t+1} \) or \( \hat{k}_{t+2} \) and the estimated livestock mortality \( \hat{m} = \hat{m}(n_{t+1}, n_i) : \)

\[ p_{Oi} = \begin{cases} \max \{0, p, k_{t+1}(\hat{m}(n_{t+1}, n_i) - \overline{m}) \} & \text{if } \hat{k}_{t+1} > 0 \\ \max \{0, p, k_{t+2}(\hat{m}(n_{t+1}, n_i) - \overline{m}) \} & \text{if } \hat{k}_{t+2} > 0 \end{cases} \]

(4)

---

7 It is interesting to know whether households would follow this rule. They may prefer paying smaller insurance premiums twice in a year rather than paying larger premium once in a year, especially if they faced severe budget constraint in a sale period, which is a dry season. Even if the insurance company tried to prevent this double purchase by checking customer’s ID, a household might buy the insurances twice with different household member names.
IBLI has two different geographically distinct insurance contracts, one each for Upper Marsabit and Lower Marsabit, which have different insurance premiums and different area coverages for s??? purposes. We set insurance premium \( p_{i,t+1,t+2} \) to those IBLI sold for in its first sales period from January to February 2010:

\[
p_{i,t+1,t+2} = 0.055 p_i k_{i,t+1,t+2} \text{ for Upper Marsabit}
\]

\[
p_{i,t+1,t+2} = 0.0325 p_i k_{i,t+1,t+2} \text{ for Lower Marsabit}
\]

where 0.055 and 0.0325 are insurance premium rates for Upper and Lower Marsabit contracts, respectively. The monetary value of 1 TLU \( (p_i) \) was ???'ly set at 15,000 Kenyan Shillings (around 187 US dollars in February 2010).

The insurance company announces the following function of the predicted livestock mortality index:

\[
m_t = \hat{m}(n_{t-1}, n_t)
\]

In order to obtain the predicted livestock mortality index, the insurance company uses the following aggregated NDVI variables: Standardized NDVI, \( \text{zndvi}_i \), for pixel \( i \) for decad \( d \) is

\[
\text{zndvi}_{id} = \frac{\text{ndvi}_{id} - E_d(\text{ndvi}_{id})}{\sigma_d(\text{ndvi}_{id})}
\]

where \( E_d(\text{ndvi}_{id}) \) and \( \sigma_d(\text{ndvi}_{id}) \) is mean and standard error of NDVI for pixel \( i \) \( (\text{ndvi}_i) \) over dekads from 1982 to 2008. \( \text{zndvi} \) for area \( a \) for decad \( d \) \( (\text{zndvi}_{ad}) \) is the average of \( \text{zndvi}_{id} \) over pixel \( i \) within area \( a \). For estimating livestock mortality in area \( a \) in season \( t \), Chantarat et al. (2009b) construct four kinds of cumulative values of \( \text{zndvi}_{ad} \) over dekads within season \( t \) and season \( t+1 \). The most important one is

\[
C_{\text{zndvi}}_{pos,ad} = \sum_{d \in T_{pos}^t} \text{zndvi}_{id}
\]

where \( T_{pos}^t \) is the set of dekadalas from October to September if season \( t \) is LRLD and from March to February if it is SRSD. Note that the insurance company starts reading NDVI for a contract for particular seasons before its sale period. For example, for a contract sold in January-February 2010, the insurance company started reading NDVI from October 2009 until September 2010 for an indemnity payout in October 2010. For another indemnity payout

---

8 The second one is

\[
C_{\text{zndvi}}_{pre,ad} = \sum_{d \in T_{pre}^t} \text{zndvi}_{id}
\]

where \( T_{pre}^t \) is the set of dekadalas from the first decad of October to the first decad of March if season \( I \) is LRLD and from the first decad of March to the first decad of October if it is SRSD. The third one is

\[
C_{\text{NZndvi}}_{ad} = \sum_{d \in T^t} \text{min}\{\text{zndvi}_{ad}, 0\}
\]

where \( T^t \) is the set of dekadalas from March to September if season \( I \) is LRLD and from October to February if it is SRSD. The forth and last one is

\[
C_{\text{Pzndvi}}_{ad} = \sum_{d \in T^t} \text{max}\{\text{zndvi}_{ad}, 0\}
\]
in March 2011, the insurance company reads NDVI from March 2010 to February 2011.

The predicted livestock mortality function \( \hat{m} (\cdot) \) specified for the IBLI contract was estimated by using NDVI data and livestock mortality data from Arid Land Resource Management Program (ALRMP) in the area in the past. The insurance company and prospective purchasers take this function as given.

The next subsection defines the timing of events and the household’s decision problem with IBLI.

4.2.1 Household’s decision problem with IBLI

The timing of the events is as follows. An insurance company offers the index-based livestock insurance contract \( I(\tilde{m}, p_{ilt+1,t+2}, P_{olt+1}, P_{olt+2}, n_t, n_{t-1}, \hat{m} (\cdot), \tilde{k}_{ilt+1}, \tilde{k}_{ilt+1,t+2} ) \) to household \( i \) in the beginning of the season \( t \). If the household has already bought the insurance in the previous season and insured livestock for season \( t \) and season \( t+1 \), that is, \( \tilde{k}_{ilt+1} > 0 \), the household cannot buy the insurance in the current season and insure livestock for season \( t+1 \) and season \( t+2 \). If household \( i \) did not buy the insurance in the previous season, household \( i \) decides the amount of livestock to be insured \( \tilde{k}_{ilt+1,t+2} \) and pays the price of the insurance \( p_{ilt+1,t+2} \). At the same time, household \( i \) decides net livestock investment \( i_t \) and consumption \( c_t \) given non-livestock income \( y_{alt} \). Livestock size in the beginning of the next season \( t+1 \) is determined by the livestock law of motion equation (1) Then, in the following season \( t+1 \), nature draws \( n_{t+1} \) given \( n_t \) and \( n_{t-1} \), then birth rate \( b_{ilt} \) and mortality shocks \( (\theta_{ilt}, \xi_{ilt}) \).

The insurance company provides payout \( p_{olt+1} \) to the household based on the contract \( I(\cdot) \), the amount of insured livestock value \( \tilde{k}_{ilt+1,t+2} \) and the estimate livestock mortality \( \hat{m}_{ilt+1} = \hat{m}(n_{ilt+1}, n_t) \) as in equation (4). In season \( t+1 \), household \( i \) cannot buy insurance if it bought insurance at season \( t \).

The household’s maximization problem in the middle of season \( t \) is summarized in the following Bellman equation:

\[
V_{IBLI,t} = \max_{i_t, \tilde{k}_{ilt+1,t+2}} u(c_t) + \beta EV_{IBLI,t+1}
\]

s.t.
\[
\begin{align*}
&c_t + p_i + p_{ilt+1,t+2} \\
&= f(k_t) + y_{alt} + p_{olt} \\
&k_{ilt+1} = k_t + i_t + b_t k_t - (\theta_t + \xi_t) k_t \\
&\tilde{k}_{ilt+1,t+2} \geq 0 \\
&\tilde{k}_{ilt+1,t+2} = 0 \text{ if } \tilde{k}_{ilt+1} > 0
\end{align*}
\]

given \( k_t, m_t, n_t, n_{t-1}, \tilde{k}_{ilt+1}, y_{alt}, b_t, \theta_t, \xi_t, I(\cdot) \)

where
\[ V_{IBLI} = V_{IBLI}(k_{it}, m_i, n_i, n_{i-1}, k_{i,t-1}, y_{nt}, b_{it}, \theta, \xi, \zeta) \]

\[ EV_{IBLI, t+1} = EV_{IBLI}(k_{i,t+1}, m_{i,t+1}, n_i, n_{i-1}, k_{i,t-1}, k_{t+1}, y_{nt+1}, b_{i,t+1}, \theta_{i,t+1}, \xi_{i,t+1}) \]

\[ = \int \int \int V_{IBLI}(k_{i,t+1}, m_{i,t+1}, n_i, n_{i-1}, k_{i,t-1}, k_{t+1}, y_{nt+1}, b_{i,t+1}, \theta_{i,t+1}, \xi_{i,t+1}) \]

\[ g_n(b_{it} | n_i, n_{i-1}) g_{\theta}(\theta_{it} | n_i, n_{i-1}) g_{\xi}(\xi_{it} | n_i, n_{i-1}) g_n(n_i | n_{i-1}, n_{i-2}) \]

\[ db_{it} d\theta_{it} d\xi_{it} d\xi_{it} \]

Denote the solution of this problem by \( \widetilde{k}_{it}^* \) and \( i_{IBLI}^* \) and the value function by \( V_{IBLI} \). Based on \( i_{IBLI}^* \) and \( V_{IBLI} \), we evaluate the effects of IBLI on household investment decision and welfare. The expected welfare effect of IBLI is \( V_{IBLI}(k_{it}, m_i, n_i, n_{i-1}, k_{i,t-1} = 0, k_{i,t+1} = 0, y_{nt}, b_{it}, \theta_{it}, \xi_{it}) - V_A(k_{it}, m_i, n_i, n_{i-1}, y_{nt}, b_{it}, \theta_{it}, \xi_{it}) \).

5 Data

We use Pastoral Risk Management (PARIMA) project data, livestock mortality data from Kenyan government ALRMP, and National Aeronautics and Space Administration (NASA) / National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) NDVI data to which we fit the model. We use PARIMA data for the four study sites in Marsabit District where IBLI is piloted. PARIMA’s North Horr study site is located in the area of IBLI’s Upper Marsabit contract while the other 3 study sites (Diriib Gombo, Kargi, Logologo) are located in the area of IBLI’s Lower Marsabit contract. Marsabit is the one of the least developed and the poorest areas in Kenya. Diriib Gombo is located in Marsabit Mountain and households there engage in crop farming in rainy seasons as well as livestock herding. The other 3 study sites are in dry lowland area and households depend on livestock as the primary and dominant economic activity. The PARIMA run household panel data quarterly from July 2000 to June 2002. We can construct household data over 4 seasons (2 LRLD and 2 SRSD seasons).

NASA/NOAA AVHRR NDVI from 1981-2010 and ALRMP livestock mortality data permit us to recover the stochastic structure of livestock and vegetation, more particularly, transition function of \( Czndvi_{post} \) and the relationship between vegetation condition \( Czndvi_{post} \) and covariate livestock shock \( \xi_i \) as specified in section 5.1 below.

Figure 1 shows the net livestock investment when \( Czndvi_{post} \geq 0 \) and \( Czndvi_{post} < 0 \).

Figure 2 shows the relationship between actual livestock mortality for each household and predicted area-average livestock mortality. The horizontal axis represents predicted area-average livestock mortality while the vertical axis represents actual livestock mortality for each household. The scatter plot (blue dots) shows each household’s actual livestock mortality given predicted area-average livestock mortality. The red line shows the LOWESS estimate of actual livestock mortality.
6 Empirical method
We fit the structural model to the data in two steps. First, we estimate a milk production function and the livestock transition function separately and directly from the household data. Second, we calculate optimal investment and insurance purchase decisions based on the first-step estimates.

6.1 Estimate Stochastic Livestock Transition Function
As mentioned above, we assume that NDVI in only the preceding two seasons \((n_{t-2}, n_{t-1})\) affect the value of NDVI in the current season \(n_t\). Furthermore, we treat cumulative standardized NDVI over the two seasons as the representative and the most important environmental variable for the forage condition and thus livestock milk production and mortality. As such, instead of recovering \(g_n(n_t | n_{t-2}, n_{t-1})\), we will recover

\[
C_{\text{ndvi}}_{\text{pos}, t} \sim g_{C_{\text{ndvi}} \sim \text{pos}}(C_{\text{ndvi}}_{\text{pos}, t} | C_{\text{ndvi}}_{\text{pos}, t-1}).
\]

In order to recover \(g_{C_{\text{ndvi}} \sim \text{pos}}(C_{\text{ndvi}}_{\text{pos}, t} | C_{\text{ndvi}}_{\text{pos}, t-1})\), we discretize \(C_{\text{ndvi}}_{\text{pos}}\) as in Table 1 and estimate empirical distribution of \(g_{C_{\text{ndvi}} \sim \text{pos}}(C_{\text{ndvi}}_{\text{pos}, t} | C_{\text{ndvi}}_{\text{pos}, t-1})\) from the data.

We assume the probability distribution of \(b_{it}\), \(\theta_{it}\), and \(\xi_t\) are functions of \(n_{t-1}\) and \(n_t\):

\[
b_{it} \sim g_{b_{it}}(b_{it} | n_{t-1}, n_t)
\]

\[
\theta_{it} \sim g_{\theta_{it}}(\theta_{it} | n_{t-1}, n_t)
\]

\[
\xi_t \sim g_{\xi}(\xi_t | n_{t-1}, n_t).
\]

Again, instead of the vectors of dekad NDVI values over season \(t - 1\) and season \(t\) \((n_{t-1}, n_t)\),

---

9 We fix the remaining unknown parameter \(\theta_{a}\) at 1.5 instead of estimating it. We could estimate it by searching for the value that minimizes the difference between observed investment in the data and computed investment but we leave it in order to decrease computing time.

10 \(n_t\) is the vector of dekad or 10-day NDVI. For example, NASA/NOAA AVHRR NDVI are dekadal data but we simplify the sequence of NDVI over season \(t\) into one aggregated variable,

\[
C_{\text{ndvi}}_{\text{current}, t} = \sum_{d \in T_{\text{current}}} \text{ndvi}_{ad}
\]

where \(T_{\text{current}}\) is the set of dekads from March to September if season \(t\) is LRLD and from October to February if it is SRS. Note that

\[
C_{\text{ndvi}}_{\text{pos}, t} = C_{\text{ndvi}}_{\text{current}, t-1} + C_{\text{ndvi}}_{\text{current}, t}.
\]

Instead of recovering

\[
n_t \sim g_n(n_t | n_{t-2}, n_{t-1})
\]

and

\[
C_{\text{ndvi}}_{\text{current}, t} \sim g_{C_{\text{ndvi}} \sim \text{current}}(C_{\text{ndvi}}_{\text{current}, t} | C_{\text{ndvi}}_{\text{current}, t-2}, C_{\text{ndvi}}_{\text{current}, t-1})
\]

we will recover

\[
C_{\text{ndvi}}_{\text{pos}, t} \sim g_{C_{\text{ndvi}} \sim \text{pos}}(C_{\text{ndvi}}_{\text{pos}, t} | C_{\text{ndvi}}_{\text{pos}, t-1}).
\]
we use cumulative standardized NDVI over the same periods $Czndvi_{pos,t}$ as the state variable that affects forage conditions and livestock births and deaths:

$$b_{it} \sim g_{b}(b_{it} \mid Czndvi_{pos,t})$$

$$\theta_{it} \sim g_{\theta}(\theta_{it} \mid Czndvi_{pos,t})$$

$$\xi_{i} \sim g_{\xi}(\xi_{i} \mid Czndvi_{pos,t})$$

In the data, we observe livestock mortality as the sum of covariate (area-average) livestock mortality $\xi_{i}k_{it}$ and idiosyncratic livestock mortality $\theta_{it}k_{it}$. In this paper, we assume that the value of $\xi_{i}k_{it}$ is the predicted mortality of the IBLI contract and idiosyncratic livestock mortality $\theta_{it}k_{it}$ is the difference between observed livestock mortality $(\theta_{it} + \xi_{i})k_{it}$ in the data and $\xi_{i}k_{it}$ 11.

In order to recover $g_{Czndvi_{pos,t}}(Czndvi_{pos,t} \mid Czndvi_{pos,t-1}), g_{\xi}(\xi_{i} \mid Czndvi_{pos,t}), g_{\theta}(\theta_{it} \mid Czndvi_{pos,t}),$ and $g_{b}(b_{it} \mid Czndvi_{pos,t})$, we discretize $Czndvi_{pos,t}$, $\xi_{i}$, $\theta_{it}$, and $b_{it}$ as in Table 1 and calculate the empirical distributions from the discretized data. Tables 2 and 3 show the distribution of $g_{Czndvi_{pos,t}}(Czndvi_{pos,t} \mid Czndvi_{pos,t-1})$ as transition matrices. Figures 3 and 4 show the distribution of $g_{\xi}(\xi_{i} \mid Czndvi_{pos,t})$ in North Horr and the other 3 study areas, respectively. Figures 5 and 6 show the distributions of $g_{\theta}(\theta_{it} \mid Czndvi_{pos,t})$ and $g_{b}(b_{it} \mid Czndvi_{pos,t})$, respectively.

6.2 Milk Production Estimates

The milk production function $f(k_{it}, n_{it}, n_{i}) = f(k_{it}, Czndvi_{pos,t})$ is estimated in the following regression equations:

$$\ln f = \beta_{0g} + \beta_{1g} \ln k_{it} \text{ when } Czndvi_{pos,t} \geq 0$$

$$\ln f = \beta_{0b} + \beta_{1b} \ln k_{it} \text{ when } Czndvi_{pos,t} < 0$$

where the subscripts $g$ and $b$ represent “good” and “bad” seasons, respectively. Tables 4 and 5 and Figure 7 show the results.

6.3 Computing the optimal investment and insurance purchase decisions

We compute the optimal investment and insurance purchase decisions as follows. The investment decision without index based livestock insurance is a simpler version of the decision problem and thus we omit the explanation about it.

---

11 A more complicated way of modeling covariate idiosyncratic livestock mortality is as follows. Take the area-average mortality $(\theta_{it} + \xi_{i})k_{it}$ and denote it as $E[(\theta_{it} + \xi_{i})k_{it}]$. This is covariate livestock mortality. Idiosyncratic livestock mortality $\theta_{it}k_{it}$ is $(\theta_{it} + \xi_{i})k_{it} - E[(\theta_{it} + \xi_{i})k_{it}]$. Predicted livestock mortality (the index of IBLI) tries to predict $E[(\theta_{it} + \xi_{i})k_{it}]$ but there is always a difference between the index and $E[(\theta_{it} + \xi_{i})k_{it}]$. The difference is a stochastic variable. Although this modeling is more rigorous, the number of variables in the model increases by 2 and one of the added variables is stochastic. We leave this extension of the model to future research.
Denote state variables \((k_a, m_i, n_t, n_{t-1}, k_{t-1}, y_{s}, b_{a}, \theta_{i}, \xi_{i})\) by \(s_{jt}\) and drop the subscript \(j\) and \(t\) for notational simplicity. We compute the value function by the following iterations:

- Discretize state space (the set of all possible states) \(s\) into \(s_1, s_2, ..., s_n\).
- Set \(V(s_q) = 0\) for all \(q = 1, 2, ..., n\) and \(\varepsilon = 0.4\).
- Denote the number of value function iteration by \(l\).
- Set \(l = 0\).
- Repeat the following until \(||V_{i+1}(s) - V_i(s)|| < \varepsilon\) holds for every \(s\):\(^{12}\)
  For \(q = 1, ..., n\), compute \((i_q, \tilde{k}_{i+1+2,q})\) which solve the following problem:

\[
V_{\text{BL}l+1}(s_q) = \max_{i_q, \tilde{k}_{i+1+2,q}} u(c_q) + \beta EV_{\text{BL}l+1}(s')
\]

s.t. \(c_q + pi_q + p_{i+1+2} = f(k_q) + y_{a} + p\)
\(k = k_q + i_q + b_k k_q - (\theta_q + \xi_q) k_q\)
\(k_i \geq 0\)
\(\tilde{k}_{i+1+2,q} \geq 0\)
\(\tilde{k}_{i+1+2,q} = 0\) if \(\tilde{k}_{i+1,q} > 0\)

Go forward to next iteration \(l + 1\).

- The value function \(V_{\text{BL}l+1}\) is defined by the final \(V_{\text{BL}l+1}\).

The policy function is defined as follows:

\[(i(s_q), \tilde{k}_{i+1+2,q}) \equiv \arg\max_{i_q, \tilde{k}_{i+1+2}} \{u(c_q) + \beta EV_{\text{BL}l+1}(s')\}\]

given the constraints above.

We discretize the state variables and control variables as in Table 1. The total number of possible states is \(432,000 = 15 \times 2 \times 4 \times 3 \times 4 \times 5 \times 4 \times (2 \times 8 - 1)\). Note that \((2 \times 8 - 1)\) is due to that both \(\tilde{k}_{i+1}\) and \(\tilde{k}_{i+1} \) cannot be positive at the same time.

We need to computationally solve the decision problem above for both index based livestock insurance contract for North Horr and one for the other 3 study areas. In order to compute the value function for each state, we simulate the utility path over 100 seasons 100 times and take the average sum of time discounted utilities over the 100 simulations.\(^{13}\) It took 128 value

---

\(^{12}\) An alternative is as follows: Repeat the following until \(||V_{i+1} - V_i|| < \varepsilon\) holds.

\(^{13}\) The number of possible states is too large to compute \(V = (I - \beta TM)^{-1} u\) where \(V\) is a vector of the values of value
function iterations and 40 hours using fortran 90 on the Intel Core 2 Duo processor (?? MHz).

7 Policy simulation Results

In this section, we report the counter-factual simulations of index-based livestock insurance and quantify the effects of the insurance offer on household intertemporal behavior and welfare. The following findings from our model simulations suggests benefits from IBLI that might easily be overlooked in the absence of a dynamic behavioral model.

Table 8 shows investment and insurance purchase decisions for different level of non-livestock income. IBLI is more beneficial for vulnerable households with less non-livestock income (which is non-stochastic and safe income source in our model) as an alternative insurance mechanism. In the numerical example, actually only the household with zero non-livestock income would purchase the insurance. Table 9 shows investment and insurance purchase decisions for different herd sizes. Note that for some herd sizes, the insured herd size \( \tilde{k}^* \) is larger than the owned herd size \( k \), which implies that households might optimally insure herd sizes larger than they own as insurance against covariate income shocks more broadly.

A key finding is that for all herd sizes households divest livestock and buy insurance. This implies that households would stabilize future income paths by using IBLI rather than by investing in livestock or consuming more in current season. Note that in the numerical example, households do not have non-livestock income \( y_{alt} \) and vegetation condition is bad \( (Czndv_{pos,j} = -5 , \) which brings bad vegetation condition in the next season more likely) and thus the example can be an extreme case and this interpretation cannot apply to other cases with different values of state variables.

Table 10 shows investment and insurance purchase decisions under different vegetation conditions, \( Czndv_{pos,j} \). Households optimally seek to buy more insurance when current vegetation conditions are bad and they expect poor range conditions – and thus a higher livestock mortality rate and indemnity payout – in the following season. If the insurance company does not (i) adjust pricing as baseline range conditions change, and (ii) use an index that is conditional on range conditions as of the contract sales date – a design feature of the actual IBLI contract –then the index insurance product and the insurer could be vulnerable to intertemporal adverse selection that has thus far received negligible attention in the rapidly growing literature on index insurance.

One of our main questions is whether households accumulate more livestock when they gain access to IBLI. They do not have to accumulate livestock as buffer stock since their income paths are more stable due to IBLI. On the other hand, since households have more stable income source due to IBLI, household may invest in livestock more since its expected returns increase with predicted ??? insurance. All of the numerical results show that households would invest less (divest more) in livestock, implying that asignificant share of stocking is for precautiooanl savings puopose that are partly ???ted by IBLI. If the livestock

\[
I \quad \text{is identity matrix,} \quad T M \quad \text{is state transition matrix, and} \quad u \quad \text{is a vector of utility values for all states.}
\]
stocking density in the region is near the level where herd increases could degrade the rangeland environment and thereby hurt livestock productivity (Desta and Coppock 2002, Fafchamps 1998), decreased livestock stocking density due to IBLI would yield a win-win-win result: reduced risk exposure, greater environmental protection, and enhanced productivity.

8 Conclusion

Index based agricultural insurance collects attention as a potentially effective tool for reducing vulnerability of agricultural households and also as a new commercially sustainable product in insurance industry. The economic literature on index based agricultural insurance has not studied dynamic effects of index based agricultural insurance on household intertemporal decisions and welfare in the long run. Chantarat et al. (2009a) is the exception and they study the effects of Index Based Livestock Insurance in Marsabit, Kenya on household welfare in the long run. This paper complements their study by accommodating household’s behavioral changes, more particularly, change in livestock investment decision and when (under what condition) they would buy the insurance and how much of their livestock herd they would insure. We construct a dynamic household decision model and fit the model to household panel data and vegetation data in the region. Our results imply that households would accumulate less livestock since their income stream would be stabilized by the insurance and do not need to accumulate livestock as buffer stock. Our results also imply that households would buy the insurance more when the current vegetation condition is bad and they expect bad vegetation condition in the following season. It suggests that we need to investigate the magnitude of this problem more and whether insurance companies need to modify the insurance contract design to alleviate the problem.

Considerable efforts are underway in several countries to pilot index-based insurance products (Barnett and Mahul 2007; see also the Index Insurance Innovations Initiative web site: http://i4.ucdavis.edu/about/). It necessarily takes several years, at least, to pilot and evaluate the impacts of such interventions. Our approach in this paper is to evaluate the impact ex ante by constructing a dynamic structural model of household behavior, fitting the model to data, and implementing counterfactual policy simulations so as to generate early predictions of the likely effects on household intertemporal decisions and welfare of the introduction of index-based livestock insurance. These simulations underscore that there may be strong reasons to anticipate behaviors and effects – such as reduced precautionary savings or intertemporal adverse selection – not commonly discussed in the research and policy dialogues around index insurance to date.
References


Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Calum G. Turvey (2009a) ‘Effectiveness of index based livestock insurance for managing asset risk and improving welfare dynamics in northern kenya.’ mimeo

Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Michael R. Carter (2009b) ‘Designing index based livestock insurance for managing asset risk in northern kenya.’ mimeo


Tables

Table 1: Discretization

State variables
\[ k_r = \{0,0.5,1.0,1.5,\cdots,3.0,4.0,\cdots,12.0\} \]
\[ m_r = \{4,5\} \]
\[ Czndvi_{pos} = \{-15,-5,5,15\} \]
\[ y_{alt} = \{0,0000,20000\} \]
\[ b_s = \{0,0.1,0.2,0.3\} \]
\[ \theta_s = \{-0.2,-0.1,0,0.1,0.2\} \]
\[ \xi_s = \{0,0.1,0.2,0.3\} \]
\[ k_{r,t} = \{0,1.0,2.0,3.0,5.0,7.0,\cdots,11.0\} \]
\[ k_{t+1,t} = \{0,1.0,2.0,3.0,5.0,7.0,\cdots,11.0\} \]

Control variables
\[ i_t = \{-0.2,-0.1,0,0.1,0.2\} \]
\[ \hat{k}_{r+1,t+2} = \{0,1.0,2.0,3.0,5.0,7.0,\cdots,11.0\} \]

Table 2: Transition Matrix of Czndvi_{pos} in North Horr from 1982-2009

<table>
<thead>
<tr>
<th>Czndvi_{pos}</th>
<th>-15</th>
<th>-5</th>
<th>5</th>
<th>15</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15</td>
<td>66.67</td>
<td>13.33</td>
<td>20.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>-5</td>
<td>45.45</td>
<td>27.27</td>
<td>18.18</td>
<td>9.09</td>
<td>100.00</td>
</tr>
<tr>
<td>5</td>
<td>0.00</td>
<td>30.77</td>
<td>30.77</td>
<td>38.46</td>
<td>100.00</td>
</tr>
<tr>
<td>15</td>
<td>7.14</td>
<td>14.29</td>
<td>21.43</td>
<td>57.14</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td>30.19</td>
<td>20.75</td>
<td>22.64</td>
<td>26.42</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 3: Transition Matrix of Czndvi_{pos} in Dirib Gombo, Kargi, Logologo from 1982-2009

<table>
<thead>
<tr>
<th>Czndvi_{pos}</th>
<th>-15</th>
<th>-5</th>
<th>5</th>
<th>15</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15</td>
<td>52.27</td>
<td>31.82</td>
<td>9.09</td>
<td>6.82</td>
<td>100.00</td>
</tr>
<tr>
<td>-5</td>
<td>28.00</td>
<td>44.00</td>
<td>12.00</td>
<td>16.00</td>
<td>100.00</td>
</tr>
<tr>
<td>5</td>
<td>27.27</td>
<td>22.73</td>
<td>18.18</td>
<td>31.82</td>
<td>100.00</td>
</tr>
<tr>
<td>15</td>
<td>6.98</td>
<td>18.60</td>
<td>18.60</td>
<td>55.81</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td>28.93</td>
<td>30.82</td>
<td>13.84</td>
<td>26.42</td>
<td>100.00</td>
</tr>
</tbody>
</table>
Table 4: Estimation results: Milk Production Function $f$ for $Czdvi_{pos,t} \geq 0$

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>(Std. Err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{bg}$</td>
<td>8.150**</td>
<td>(0.210)</td>
</tr>
<tr>
<td>$\beta_{bg}$</td>
<td>0.347**</td>
<td>(0.080)</td>
</tr>
<tr>
<td>N</td>
<td>139</td>
<td></td>
</tr>
<tr>
<td>R 2</td>
<td>0.122</td>
<td></td>
</tr>
<tr>
<td>F (1,137)</td>
<td>18.958</td>
<td></td>
</tr>
</tbody>
</table>
Significance level: **: 1%

Table 5: Estimation results: Milk Production Function $f$ for $Czdvi_{pos,t} < 0$

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>(Std. Err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{ob}$</td>
<td>7.672**</td>
<td>(0.211)</td>
</tr>
<tr>
<td>$\beta_{ib}$</td>
<td>0.446**</td>
<td>(0.073)</td>
</tr>
<tr>
<td>N</td>
<td>172</td>
<td></td>
</tr>
<tr>
<td>R 2</td>
<td>0.179</td>
<td></td>
</tr>
<tr>
<td>F (1,170)</td>
<td>37.123</td>
<td></td>
</tr>
</tbody>
</table>
Significance level: **: 1%

Table 8: $i^{*}_A$, $i^{*}_{BLJ}$, and $\tilde{k}^{*}$ by $y_{al}$ in North Horr

<table>
<thead>
<tr>
<th>$y_{al}$</th>
<th>$i^{*}_A$</th>
<th>$i^{*}_{BLJ}$</th>
<th>$\tilde{k}^{*}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.0</td>
<td>-0.1</td>
<td>3.0</td>
</tr>
<tr>
<td>10,000</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>20,000</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Other variables are fixed as follows: $k_i = 4.0$, $m_i = 4$, $b_i = 0.1$, $\theta_{it} = 0.0$, $s_{it} = 0.1$, $Czdvi_{pos,t} = -5.0$, $\tilde{k}_{t-1,t} = 0.0$, $\tilde{k}_{t-1,t} = 0.0$.

Table 9: $i^{*}_A$, $i^{*}_{BLJ}$, and $\tilde{k}^{*}$ by $k$ in North Horr

<table>
<thead>
<tr>
<th>$k$</th>
<th>$i^{*}_A$</th>
<th>$i^{*}_{BLJ}$</th>
<th>$\tilde{k}^{*}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>-0.1</td>
<td>-0.2</td>
<td>2.0</td>
</tr>
<tr>
<td>1.5</td>
<td>0.0</td>
<td>-0.1</td>
<td>2.0</td>
</tr>
<tr>
<td>2.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>2.0</td>
</tr>
<tr>
<td>3.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>2.0</td>
</tr>
<tr>
<td>4.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>3.0</td>
</tr>
<tr>
<td>5.0</td>
<td>-0.1</td>
<td>-0.2</td>
<td>9.0</td>
</tr>
<tr>
<td>6.0</td>
<td>0.1</td>
<td>-0.2</td>
<td>9.0</td>
</tr>
</tbody>
</table>
7.0  -0.1  -0.2  11.0  
8.0  0.0  -0.1  7.0  
9.0  0.0  -0.1  7.0  
10.0 0.0  -0.1  9.0  
11.0 0.0  -0.1  9.0  

Other variables are fixed as follows: $m_t = 4$, $y_{alt} = 0$, $b_t = 0.1$, $\theta_{it} = 0.0$, $\zeta_t = 0.1$, $Czndvi_{pos} = -5.0$, $\bar{k}_{t-1,i} = 0.0$, $\bar{k}_{t,i+1} = 0.0$.

**Table 10:** $i^*_A$, $i^*_{IBLI}$, and $\bar{k}^*$ by $Czndvi_{pos}$ in North Horr

<table>
<thead>
<tr>
<th>$Czndvi_{pos}$</th>
<th>$i^*_A$</th>
<th>$i^*_{IBLI}$</th>
<th>$\bar{k}^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>3.0</td>
</tr>
<tr>
<td>-5.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>3.0</td>
</tr>
<tr>
<td>5.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>15.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Other variables are fixed as follows: $k_i = 4.0$, $m_t = 4$, $y_{nh} = 0$, $b_t = 0.1$, $\theta_{it} = 0.0$, $\zeta_t = 0.1$, $\bar{k}_{t-1,i} = 0.0$, $\bar{k}_{t,i+1} = 0.0$, $\bar{k}_{t,i+1} = 0.0$.  

18
Figures

**Figure 1: Net Livestock Investment**
The number of observation is 364. “1” is the histogram of net livestock investment when $C_{\text{ndvi}_{\text{posit}}} \geq 0$. The number of observation of this group is 139. “0” is the histogram of net livestock investment when $C_{\text{ndvi}_{\text{posit}}} < 0$. The number of observation of this group is 172.

**Figure 2: Predicted and Actual Mortality Rates in all study areas**
The number of observation is 364.

**Figure 3: Histograms of Predicted Covariate Mortality Shock $\zeta_i$ by $C_{\text{ndvi}_{\text{posit}}} \geq 0$ or $C_{\text{ndvi}_{\text{posit}}} < 0$ in North Horr**
The number of observation is 54. “1” is the histogram of $\theta_{a}$ with $C_{\text{ndvi}_{\text{posit}}} \geq 0$. The number of observation of this group is 27. “0” is the histogram of $\theta_{a}$ with $C_{\text{ndvi}_{\text{posit}}} < 0$. The number of observation of this group is 27.
Figure 4: Histograms of Predicted Covariate Mortality Shock $\xi_i$ by $Czendvi_{\text{posit}} \geq 0$ or $Czendvi_{\text{posit}} < 0$ in Dirib Gombo, Kargi, Logologo

The number of observation is 162. “1” is the histogram of $\theta_{\text{posit}}$ with $Czendvi_{\text{posit}} \geq 0$. The number of observation of this group is 65. “0” is the histogram of $\theta_{\text{posit}}$ with $Czendvi_{\text{posit}} < 0$. The number of observation of this group is 97.

Figure 5: Histograms of Individual Livestock Mortality Shock $\theta_{\text{lit}}$ by $Czendvi_{\text{posit}} \geq 0$ or $Czendvi_{\text{posit}} < 0$

The number of observation is 364. “1” is the histogram of $\theta_{\text{lit}}$ with $Czendvi_{\text{posit}} \geq 0$. The number of observation of this group is 153. “0” is the histogram of $\theta_{\text{lit}}$ with $Czendvi_{\text{posit}} < 0$. The number of observation of this group is 211.

Figure 6: Histograms of Individual Livestock Birth Rate Shock $b_{\text{lit}}$ by $Czendvi_{\text{posit}} \geq 0$ or $Czendvi_{\text{posit}} < 0$

The number of observation is 364. “1” is the histogram of $b_{\text{lit}}$ with $Czendvi_{\text{posit}} \geq 0$. The number of observation of this group is 153. “0” is the histogram of $b_{\text{lit}}$ with $Czendvi_{\text{posit}} < 0$. The number of observation of this group is 211.
Figure 7: Milk Production Function \( y_i \) by \( Czndvi_{pos,It} \geq 0 \) or \( Czndvi_{pos,It} < 0 \)

The number of observation is 364. “1” is the histogram of \( \theta_{It} \) with \( Czndvi_{pos,It} \geq 0 \). The number of observation of this group is 139. “0” is the histogram of \( \theta_{It} \) with \( Czndvi_{pos,It} < 0 \). The number of observation of this group is 172.

Figure 8: \( i_A^*, i_{IBLI}^* \) by \( k \) in North Horr

Other variables are fixed as follows: \( m_i = 4, y_{alt} = 0, b_i = 0.1, \theta_{It} = 0.0, \xi_t = 0.1, Czndvi_{posIt} = -5.0, \tilde{k}_{t-1J} = 0.0, \tilde{k}_{tJ}^0 = 0.0, \).
Figure 8: $\tilde{k}^*$ by $k$ and $y_{nt}$ in North Horr

Other variables are fixed as follows: $m_t = 4$, $b_t = 0.1$, $\theta_{nt} = 0.0$, $\xi_t = 0.1$, $Czndvi_{past} = -5.0$, $\tilde{k}_{t+1,t} = 0.0$, $\tilde{k}_{t+2,t} = 0.0$. 