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

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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 insurance, livestock, drought, pastoralists, Kenya

JEL classification: D9, O12, Q12

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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 or asset fluctuations by partially offsetting poor realizations of agricultural production or assets following the covariate shocks, 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 and invest more in productive agricultural assets and thereby increase productivity and income. Induced behavioral effects could lead to general equilibrium effects and 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 asset 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 (Desta and Coppock 2002, Fafchamps 1998). If IBLI induces increased livestock holdings, it could bring overgrazing and

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5 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, McPeak 2005).
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), Vercammen (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. On the other hand, Chantarat et al. (2009a) and Janzen, Carter, and Ikegami (2013) study the long term effects of Index Based Livestock Insurance. Chantarat et al. (2009a) do not investigate induced investment effects by assuming 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. Janzen, Carter, and Ikegami (2013) study induced investment effects of IBLI by relaxing this assumption and accommodating change in investment and purchase decisions when herd size changes and the existence of IBLI changes study induced investment effects of IBLI.

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)). Chantarat et al. (2009a) and Janzen, Carter, and Ikegami (2013) are following these previous studies and assuming poverty trap structure. However, these results are based on reduced form estimation and previous studies do not rigorously identify structures generating poverty trap herd dynamics. Also, in our data described below, there were two droughts within 6 years of survey periods and both richer and poorer households lost livestock rather than poorer households lost households and richer household accumulated livestock as a poverty trap generates. Since we could not find poverty trap evidence in our data and we could not identify the exact poverty trap structure for our structural analysis, this paper would focus on dynamic household decisions in an the economic structure without a poverty trap. We leave studying a poverty trap in our data further 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 IBLI project annual household panel data collected in Marsabit County in Northern Kenya from October 2009 to October 2013. IBLI was first sold in February 2010 and the first round of the survey data was collected four months before the first sale.

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) (Chantrat et al. 2010b) and by more recent NASA MODIS NDVI data. We use the IBLI’s regression model from Chantrat et al. (2010b), IBLI Household Survey data, and NASA MODIS NDVI data 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$^6$) in the beginning of season $t$ by $k_{it}$. In the East Africa rangeland, we study, annual rainfall is bimodal. 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

$$k_{it+1} = \max\{k_{it} + b_{it}k_{it} + p_{it}u - s_{it} - s^a_{it} - (\theta_{it} + \xi_{it})k_{it}, 0\}$$

(1)

where $b_{it}$, $p_{it}$, $s_{it}$, and $s^a_{it}$ are birth rate, purchases, slaughter for own consumption and sale of livestock, respectively. $\theta_{it}$ and $\xi_{it}$ are idiosyncratic and covariate mortality shocks, respectively. The household’s budget constraint each period is

$$c_{it} + p_t (s_{tit} + \tilde{s}_{ait}) = f_{it} + p_t (s_{tit} + \tilde{s}_{ait}) + y_{it}^{nl}$$

(2)

where $c_{it}$ is consumption of composite good, $f_{it}$ is milk income, $y_{it}^{nl}$ is time-invariant income from non-livestock production (e.g. remittances, food aid transfers, wage income), $p_t$ is the price of 1 TLU of livestock. Household own consumption of animal products is included in $c_{it}$. We assume the extreme version of credit constraints, that is, the household cannot borrow at all$^7$. Since we assume that 1 TLU is the same price regardless of whether the household

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$^6$ 1 TLU is equivalent to 1 cattle, 0.7 camel, 10 sheep, or 10 goats.

$^7$ We can relax this assumption by allowing the household to borrow some amounts up to some limit, for example, some
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 \( i_{it} = p_{it}^u - s_{it}^l - s_{it}^a \):

\[
k_{i,t+1} = \max \{ k_{it} + b_{it}k_{it} + i_{it} - (\theta_{it} + \xi_{it})k_{it}, 0 \} \quad (1')
\]

\[
c_{it} + p_{it}i_{it} = f_{it} + y_{it}^{nl} \quad (2')
\]

The covariate livestock mortality shock in this setting can be explained by vegetation condition over the rangeland. Denote the Normalized Differential Vegetation Index (NDVI), a measure of rangeland forage condition 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,

\[
n_t \sim g_u(n_t) \quad (3)
\]

where \( g_u(\cdot \mid \cdot \cdot) \) is a conditional probability density function. The probability distributions of \( b_u, \theta_u, \) and \( \xi_t \) are assumed to be functions of \( n_t \) and \( n_{t-1} \):

\[
b_u \sim g_b(b_u \mid n_{t-1}, n_t)
\]

\[
\theta_u \sim g_\theta(\theta_u \mid n_{t-1}, n_t)
\]

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

Since vegetation conditions \( (n_{t-2}, n_t) \) affect births \( b_u \), it affects milk production as well. The milk production function is defined as \( f = f(k_u, n_{t-1}, n_t) \). We assume that \( f(\cdot \cdot \cdot) \) is concave and monotonically increasing in \( k_u \) and \( f(0,n_{t-1},n_t) = 0 \).

The timing of events is as follows. In the beginning of season \( t \), given TLU, \( k_{it} \), non-livestock income, \( y_{nli} \), household \( i \) decides investment \( i_{it} \) and consumption \( c_{it} \). Then, the nature draws \( n_t \) given \( n_{t-1} \) and \( n_{t-2} \), determining the period specific birth rate \( b_u \) and negative mortality shocks \( (\theta_u, \xi_t) \). Given this realization of random variables and non-livestock income, \( y_{nli} \), 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:

\[
\max \sum_{t=1}^{\infty} \beta^{t-1} u(c_{it}) \quad (1')
\]

\[
s.t. (1'), (2')
\]

where \( u(c_{it}) = m_i \left( \frac{c_{it}}{m_i} \right)^{(1-\theta_u)} - 1 \left( 1 - \theta_u \right) \), \( m_i \) 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:

\[
V^A(k_{it}, n_{t-1}, n_{t-2}) = \max_{i_{it}} \{ u(c_{it}) + \beta E_t V^A(k_{it+1}) \}
\]

s.t. (1'), (2')

given \( k_{it}, n_{t-1}, n_{t-2}, m_i, y_{it}^{nl} \)

percentage of livestock value, without changing the qualitative findings but of the cost of added, unnecessary clutles? in the model.
where
\[
E_t V^A(k_{i,t+1}) = \int \int \int V^A(k_{i,t+1}) g_b(b_{i,t}|n_t, n_{t-1}) g_{\theta}(\theta_{i,t}|n_t, n_{t-1})
\]
\[
g_\xi(\xi_t|n_t, n_{t-1}) d\beta d\theta d\xi_t d\eta_t
\]

\[E_t\] represents expectation at period \(t\) when agent \(i\) decides investment \(i_{it}\) and consumption \(c_{it}\).

Subscript \(A\) under the value function \(V\) represents autarky, distinguishing it from economic environment with the index-based livestock insurance. We will compare this value function and its resulting behavioral functions with those when index-based livestock insurance is available. Denote the optimal net accumulation of livestock under autarky by \(i_{at}^*\).

4.2. With Index Based Livestock Insurance

4.2.1. without learning

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 \(I(\tilde{m}, p_{i,t+1}^l, p_{i,t}^o, p_{i,t+1}^o, n_{t-1}, n_t, n_{t+1}, \hat{m}(\cdot), \tilde{k}_{i,t-1}, \tilde{k}_{i,t+1})\) where \(p_{i,t+1}^l\), \(p_{i,t}^o\), and \(p_{i,t+1}^o\) are premium and indemnity payouts of the insurance, respectively, \(\tilde{k}_{i,t+1}\) is the amount (TLU) of livestock household chooses to insure for season \(t\) and season \(t+1\), \(\hat{m}(\cdot)\) is the predicted livestock mortality index, and \(\tilde{m}\) is the strike point in the index, above which the insurance company provides indemnity payouts. \(\tilde{k}_{i,t+1} = 0\) means the household does not buy the insurance. Indemnity payout \(p_{i,t}^o\) is based on the contract \(I(\cdot)\), the insured livestock value \(\tilde{k}_{i,t-1}\) or \(\tilde{k}_{i,t+1}\) and the estimated livestock mortality \(\hat{m}_t = \hat{m}(n_{t-1}, n_t)\):

\[
p_{i,t}^o = p^o(\tilde{k}_{i,t-1}, \tilde{k}_{i,t+1}, \hat{m}(n_{t-1}, n_t); I)
\]
\[
= \max\{0, p \tilde{k}_{i,t-1}(\hat{m}(n_{t-1}, n_t) - \tilde{m})\} + \max\{0, p \tilde{k}_{i,t+1}(\hat{m}(n_{t-1}, n_t) - \tilde{m})\}
\]

(4)

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 simulation Purposes, we set insurance premium \(p_{i,t+1}^l\) to those IBLI sold for in its first sales period from January to February 2010:

\[
p_{i,t+1}^l = 0.055 p \tilde{k}_{i,t+1}\text{ for Upper Marsabit}
\]
\[
p_{i,t+1}^l = 0.0325 p \tilde{k}_{i,t+1}\text{ for Lower Marsabit}
\]

where 0.055 and 0.0325 are insurance premium rates for Upper and Lower Marsabit
contracts, respectively. The monetary value of 1 TLU \((p_t)\) was 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:

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

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

\[
zndvi_{id} = \frac{ndvi_{id} - E_d(ndvi_{id})}{\sigma_d(ndvi_{id})}
\]

where \(E_d(ndvi_{id})\) and \(\sigma_d(ndvi_{id})\) is mean and standard error of NDVI for pixel \(i\) \((ndvi_{id})\) over dekads from 1982 to 2008. \(zndvi\) for area \(a\) for dekad \(d\) \((zndvi_{ad})\) is the average of \(zndvi_{id}\) 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 \(zndvi_{ad}\) over dekads within season \(t\) and season \(t+1\). The most important one is

\[
Czndvi_{posT} = \sum_{d \in T^{pos}} zndvi_{ad}
\]

where \(T^{pos}\) is the set of dekads from October to September if season \(t\) is LRLD and from March to February if it is SRSD.\(^8\) 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 in March 2011, the insurance company reads NDVI from March 2010 to February 2011.

The predicted livestock mortality function \(\hat{m}(\cdot, \cdot)\) 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 timing of the events is as follows. An insurance company offers the index-based livestock

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\(^8\) The second one is

\[
Czndvi_{preT} = \sum_{d \in T^{pre}} zndvi_{ad}
\]

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

\[
CNzndvi_{ad} = \sum_{d \in T^{t}} \min\{zndvi_{ad}, 0\}
\]

where \(T^{t}\) is the set of dekads from March to September if season \(t\) is LRLD and from October to February if it is SRSD.

The fourth and last one is

\[
CPzndvi_{ad} = \sum_{d \in T^{t}} \max\{zndvi_{ad}, 0\}
\]
insurance contract \( I(\bar{m}, p_{i,t,t+1}^l, p_{i,t,t+1}^o, n_{t-2}, n_t, n_{t-1}, \hat{m}, k_{i,t+1}, \hat{k}_{i,t+1}) \) to household \( i \) in the beginning of the season \( t \). Household \( i \) decides net livestock investment \( i_\nu \) and consumption \( c_\nu \), the amount of livestock to be insured \( \hat{k}_{i,t+1} \), and pays the price of the insurance \( p_{i,t,t+1}^o \) given TLU, \( k_{i,t} \), non-livestock income, \( y_{nlit} \), and indemnity payout in the previous season \( p_{i,t-1}^o \). Then, the nature draws \( n_t \) given \( n_{t-2} \) and \( n_{t-1} \), then birth rate \( b_{it} \) and mortality shocks \( (\theta_{it}, \xi_{it}) \). Livestock size in the beginning of the next season \( t+1 \) is determined by the livestock law of motion equation \( (1^1) \). The insurance company provides payout \( p_{i,t}^o \) to the household based on the contract \( I(\cdot) \), the amounts of insured livestock value, \( \hat{k}_{i,t-1} \) and \( \hat{k}_{i,t+1} \), and the estimate livestock mortality \( \hat{m}_t = \hat{m}(n_{t-1}, n_t) \) as in equation \( (4) \).

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

\[
V_{IBLI}^t(k_{it}, n_{t-1}, n_{t-2}, \hat{k}_{i,t-1}, t, p_{i,t-1}^o) = \max_{k_{it}, \hat{k}_{i,t-1}} \ u(c_{it}) + \beta E_t V_{IBLI}^t(k_{i,t+1}, n_{t-1}, n_{t-2}, \hat{k}_{i,t+1}, t, p_{i,t+1}^o)
\]

s.t. \( c_{it} + p_{it} + p_{i,t+1} = f(k_{it}) + y_{nlit}^n + p_{i,t+1}^o \)

\( k_{i,t+1} = \max\{k_{it} + i_{it} + b_{it}k_{it} - (\theta_{it} + \xi_{it})k_{it}, 0\} \)

\( \hat{k}_{i,t+1} = 0 \)

where

\[
E_t V_{IBLI}^t(k_{i,t+1}, n_{t-1}, n_{t-2}, \hat{k}_{i,t+1}, t, p_{i,t+1}^o) = \int \int V_{IBLI}^t(k_{i,t+1}, n_{t-1}, n_{t-2}, \hat{k}_{i,t+1}, t, p_{i,t+1}^o)
\]

\[
g_b(b_{it}|n_{t-1}, n_{t-2})g_{\theta}(\theta_{it}|n_{t-1}, n_{t-2})g_{\xi}(\xi_{it}|n_{t-1}, n_{t-2})db_{it}d\theta_{it}d\xi_{it}dn_{t}
\]

Denote the solution of this problem by \( k_{i,t+1}^*, \hat{k}_{i,t+1}^* \) 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

\[
V_{IBLI}(k_o, n_{t-1}, \hat{k}_{i,t-1} = 0, y_{nlit}, p_{i,t-1}^o = 0) - V_A(k_o, n_{t-1}, y_{nlit}) \]

We will derive optimal insurance demand and study how much the model can explain the data.

5. Data
We use IBLI Household Survey data from October 2009 to October 2013. In the data, there are 924 households from 16 sub-locations. Four sub-locations are located in the area of IBLI’s Upper Marsabit contract and its Maikona index area while the other 12 sub-locations are located in the area of IBLI’s Lower Marsabit contract and its three separate index areas called Cantral and Gadamoji, Laisamis, and Loiyangalani index areas. Marsabit is the one of the least developed and the poorest areas in Kenya. 3 sub-locations in Central and Gadamoji index area are located on Marsabit Mountain and households engage in crop farming in rainy seasons as well as livestock herding. The other 13 sub-locations are in dry lowland area and households depend on livestock as the primary and dominant economic activity. The IBLI
project run household survey annually from October 2009 to October 2013. By utilizing it
detailed recall data on each season, we can construct household data over 10 seasons (five
LRLD and five SRSD seasons).

IBLI project uses predicted livestock mortality index using 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 and more recent NASA MODIS NDVI data based on the
regression model developed by Chantarat (2009b). We use MODIS NDVI and IBLI’s
predicted livestock mortality index model but we do not use ALRMP data and AVHRR
NDVI data directly in this paper. MODIS NDVI data from 2001-2013 and IBLI’s predicted
livestock mortality index model permit us to recover the stochastic structure of IBLI index
and vegetation, more particularly, transition function of $C_{zndvi}^{pos}$ and the relationship
between vegetation condition $C_{zndvi}^{pos}$ and predicted livestock mortality index $\hat{m}$.

Table 2 shows the descriptive statistics of the data. The last two rows show that the
average of $C_{zndvi}^{pos}$ over our survey period from 2008 to 2013 is -4.48 and it is much
lower than the average over the time period from 2001 to 2008 when NDVI data are available,
0.88. This is consistent with the fact that there are two drought in 2009 and 2011 out of 6 tears
from 2008 to 2013, which was more frequent than known frequency of one drought out of
two to five years in the study area.

Figure 1 shows the net livestock investment when $C_{zndvi}^{pos} \geq -10$ and when
$C_{zndvi}^{pos} < -10$. The households increase livestock investment in non-drought seasons
slightly compared to drought seasons.

Figure 7 shows the relationship between idiosyncratic livestock mortality for each
household, $\theta_i$, and covariate sub-location-average livestock mortality, $\xi_t$. The horizontal axis
represents discretized covariate sub-location-average livestock mortality while the vertical axis
represents idiosyncratic livestock mortality for each household. The scatter plot (blue
dots) shows each household’s idiosyncratic livestock mortality given discretized sub-location-
average livestock mortality. The red, green, and orange lines show 25%, 50%, and 75%
percentiles, respectively. The variance of idiosyncratic mortality is larger when covariate
mortality is large.

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 $(n_{t-2},n_{t-1})$

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9 We fix the remaining unknown parameter $\theta_u$ 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.
affect the value of NDVI in the current season \( n_t \) \( (3) \). 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\(^{10}\)

\[
Czndvi_{post} \sim g_{Czndvi_{post}} (Czndvi_{post} | Czndvi_{post-1}).
\]

In order to recover \( g_{Czndvi_{post}} (Czndvi_{post} | Czndvi_{post-1}) \), we discretize \( Czndvi_{post} \) as in Table 1 and estimate empirical distribution of \( g_{Czndvi_{post}} (Czndvi_{post} | Czndvi_{post-1}) \) from the data.

We assume the probability distribution of \( b_t, \theta_t, \xi_t \) and \( \xi_t - \bar{m} \) are functions of \( n_{t-1} \) and \( n_t \):

\[
\begin{align*}
  b_{it} &= g_b(b_{it} | n_{t-1}, n_t) \\
  \theta_{it} &= g_\theta(\theta_{it} | n_{t-1}, n_t) \\
  \xi_t &= g_\xi(\xi_t | n_{t-1}, n_t)
\end{align*}
\]

Again, instead of the vectors of dekad NDVI values over season \( t - 1 \) and season \( t \) \( (n_{t-1}, n_t) \), we use cumulative standardized NDVI over the same periods \( Czndvi_{post} \) as the state variable of forage conditions affecting livestock births and deaths and gape between average livestock mortality and index:

\[
\begin{align*}
  b_{it} &= g_b(b_{it} | Czndvi_{post,t}) \\
  \theta_{it} &= g_\theta(\theta_{it} | Czndvi_{post,t}) \\
  \xi_t &= g_\xi(\xi_t | Czndvi_{post,t})
\end{align*}
\]

In the data, we observe livestock mortality as the sum of covariate (area-average) livestock mortality \( \xi_t k_t \) and idiosyncratic livestock mortality \( \theta_{it} k_{it} \). In this paper, we assume that the value of \( \xi_t \) is the average of observed livestock mortality rate \( (\theta_{it} + \xi_t) \) over households in season \( t \), that is, \( \xi_t = (\sum_i (\theta_{it} + \xi_t) k_{it})/(\sum_i k_{it}) \). After obtaining \( \xi_t \) from the data, we can obtain \( \theta_{it} \) as \( (\theta_{it} + \xi_t) - \xi_t \). Predicted livestock mortality (the index of IBLI, \( \bar{m} \)) tries to

\(^{10}\) \( n_t \) 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,

\[
Czndvi_{current} = \sum_{i \in T_{current}} zndvi_{i\text{d}}
\]

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

\[
Czndvi_{post} = Czndvi_{current,4} + Czndvi_{current,1}.
\]

Instead of recovering

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

and

\[
Czndvi_{current} \sim g_{Czndvi_{current}} (Czndvi_{current} | Czndvi_{current-2}, Czndvi_{current-1})
\]

we will recover

\[
Czndvi_{post} \sim g_{Czndvi_{post}} (Czndvi_{post} | Czndvi_{post-1}).
\]
predict covariate shock $\xi_t$ but there is always a difference between the index and the shock. In order to recover $g_{CznDvi_{pos} \mid CznDvi_{pos-1}}$, $g_{\xi} (\xi_{t} \mid CznDvi_{pos})$, $g_{\theta} (\theta_{u} \mid CznDvi_{pos})$, and $g_{b} (b_{u} \mid CznDvi_{pos})$, we discretize $CznDvi_{pos}$, $\xi_{t}$, $\theta_{u}$, and $b_{u}$ as in Table 3 and calculate the empirical distributions from the discretized data. Table 4 and Table 5 show the distribution of $g_{CznDvi_{pos} \mid CznDvi_{pos-1}}$ as transition matrices in Maikona index area and Lower Marsabit contract area, respectively. Figure 2 - Figure 6 shows the distribution of $m$, $g_{\xi} (\xi_{t} \mid CznDvi_{pos})$, $g_{\theta} (\theta_{u} \mid CznDvi_{pos})$, and $g_{b} (b_{u} \mid CznDvi_{pos})$, respectively.

6.2. Milk Production Estimates

The milk production function $f(k, n, i, t) = f(k, CznDvi_{pos})$ is estimated in the following regression equations:

$$\ln f_{it} = \beta_0 + \beta_1 \cdot 1\{CznDvi_{it}^{pos} \geq -10\} + \beta_2 \cdot \ln k_{it} + \beta_3 \cdot 1\{CznDvi_{it}^{pos} \geq -10\} \cdot \ln k_{it}$$

where $1\{CznDvi_{it}^{pos} \geq -10\}$ is indicator function taking 1 if $CznDvi_{it}^{pos} \geq -10$, and taking 0 otherwise. Table 6 and Figure 10 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.

Denote state variables $(k_{u}, m_{i}, n_{i}, n_{-1}, k_{u-1}, k_{i-1}, y_{t-1}, b_{u}, \theta_{u}, \xi_{t})$ by $s_{\beta}$ 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 $s_{1}, s_{2}, \ldots, s_{n}$.
- Set $V_0(s_{q}) = 0$ for all $q = 1, 2, \ldots, n$ and $\varepsilon = 0.4$.
- Denote the number of value function iteration by $l$.
- Set $l = 0$.
- Repeat the following until $||V_{l+1}(s) - V_{l}(s)|| < \varepsilon$ holds for every $s$.\(^{11}\)

For $q = 1, \ldots, n$, compute $(i_{q}, \tilde{k}_{r+1, q})$ which solve the following problem:

---

\(^{11}\) An alternative is as follows: Repeat the following until $||V_{l+1} - V_{l}|| < \varepsilon$ holds.
\[ V_{IBLI+1}(s_q) = \max_{i_q, \tilde{k}_{i+1,i+2,q}} u(c_q) + \beta EV_{IBLI}(s') \]

s.t. \( c_q + pi_q + pL_{i+1,i+2} = f(k_q) + y_{nq} + pO \)
\[ \tilde{k}' = k_q + i_q + b_qk_q - (\theta_q + \tilde{\epsilon}_q)k_q \]
\[ k_i \geq 0 \]
\[ \tilde{k}_{i+1,i+2,q} \geq 0 \]
\[ \tilde{k}_{i+1,i+2,q} = 0 \text{ if } \tilde{k}_{i+1,i+2,q} > 0 \]

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

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

The policy function is defined as follows:
\[ (i(s_q), \tilde{k}_{i+1,i+2,q}) = \arg\max_{i_q, \tilde{k}_{i+1,i+2}} \{ u(c_q) + \beta EV_{IBLI}(s') \} \]
given the constraints above.

We discretize the state variables and control variables as in Table 3. The total numbers of possible states and possible choices at each state are 38,976 and 40, respectively.

We need to computationally solve the decision problem above for each of Upper and Lower Marsabit contracts. 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. It took 128 value function iterations and 47 hours using fortran 90 on the Intel Core i5 processor (2.4 GHz).

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.

Figure 11 Error! Reference source not found. shows insurance purchase decisions at bad season \( Czndv_{t}^{pos} = -15.0 \) for different level of non-livestock income and herd size. IBLI is expected to be 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, however, Figure 11 shows that there is no apparent difference in insurance purchase decisions at bad season for different level of non-livestock income level. Note that for all herd sizes, the insured herd size \( \tilde{k}^* \) is more than the owned

\[ V = (I - \beta TM)^{-1} u \]

12 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 for all states, \( I \) is identity matrix, \( TM \) is state transition matrix, and \( u \) is a vector of utility values for all states.
herd size $k$ although they could insure less livestock than they own since insurance company does not investigate how much livestock they own for index based livestock insurance. On the other hand, Figure 14 shows that IBLI would increase the herd size in 100 seasons later and there is difference in increase among households with different non-livestock income. Based on the figure, we can say that households with less non-livestock income would obtain more benefit from IBLI than the other households.

Figure 12 shows investment decisions at bad season ($C_{zndvi_{pos}} = -15.0$) for different herd sizes under autarky and IBLI. A key finding is that for all herd sizes households divest livestock and buy insurance (Figure 11 and Figure 12). 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 $y_{nl}$ and vegetation condition is bad ($C_{zndvi_{pos}} = -15$, 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.

We expected that 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 opportunistic behavior that has thus far received negligible attention in the rapidly growing literature on index insurance. However, Figure 13 shows insurance purchase decisions under different vegetation conditions, $C_{zndvi_{pos}}$ and households do not change insured amount so much based on vegetation conditions, $C_{zndvi_{pos}}$, implying intertemporal opportunistic behavior would not be rampant.

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. Figure 14 shows the relationship between the initial livestock herd size and herd size in 100 seasons (50 years) later for different non-livestock income and under autarky and IBLI. We could expect increase in herd size due to the introduction of IBLI. If the livestock 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), increased livestock stocking density due to IBLI would yield less environmental protection and productivity although IBLI would yield a reduced risk exposure against drought.

One of our main questions is whether IBLI would increase household’s long term economic welfare or not. Figure 14 shows that IBLI would increase the herd size in 100 seasons later and the answer to the question is yes: IBLI would increase household’s long term economic welfare. Note that our model does not accommodate the negative effects of increased herd size on environment and productivity and thus our results are upper bound of
positive effects of IBLI on household’s long term welfare. Also note that although we find increased herd size in 100 hundred seasons later, we find that the investment decision in a bad season would not change so much due to the introduction of IBLI. This implies that increased herd size is partly due to more stable income flow and asset accumulation rather than increased investment.

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 more livestock. Livestock is not only a productive asset, it is also the prime form in which pastoralist households’ engage in precautionary savings. Our results imply that the former aspect of livestock dominates the latter, IBLI should induce pastoralists to increase their herd sizes as the risk of livestock loss falls.

Our results also imply that households would not buy the insurance more when the current vegetation condition is bad and they expect bad vegetation condition in the following season. It suggests that the magnitude of intertemporal opportunistic behavior would not be so rampant that 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. Basis risk, trust, and subjective belief on basis risk

<table>
<thead>
<tr>
<th></th>
<th>$\mu_{rit} &lt; 0$</th>
<th>$\mu_{rit} = 0$</th>
<th>$\mu_{rit} &gt; 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_{rit}^2$ is small</td>
<td>(1,1) mistrust on the insurance company or its product</td>
<td>(1,2) basis risk is small</td>
<td>(1,3)</td>
</tr>
<tr>
<td>$\sigma_{rit}^2$ is large</td>
<td>(2,1)</td>
<td>(2,2-3) trust on insurance company but basis risk is large</td>
<td></td>
</tr>
</tbody>
</table>

#### Table 2. Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household Size</td>
<td>9,119</td>
<td>5.9</td>
<td>2.4</td>
<td>1.0</td>
<td>17.0</td>
</tr>
<tr>
<td>TLU beginning</td>
<td>9,119</td>
<td>18.1</td>
<td>25.0</td>
<td>0.0</td>
<td>359.3</td>
</tr>
<tr>
<td>Milk production</td>
<td>9,119</td>
<td>74,774</td>
<td>108,581</td>
<td>0</td>
<td>588,000</td>
</tr>
<tr>
<td>Non-livestock Income</td>
<td>9,119</td>
<td>19,555</td>
<td>62,364</td>
<td>0</td>
<td>2,275,000</td>
</tr>
<tr>
<td>Net Investment Rate</td>
<td>8,564</td>
<td>-0.02</td>
<td>0.09</td>
<td>-0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>Birth Rate</td>
<td>8,564</td>
<td>0.10</td>
<td>0.12</td>
<td>0.00</td>
<td>0.30</td>
</tr>
<tr>
<td>Mortality Rate</td>
<td>8,564</td>
<td>0.14</td>
<td>0.23</td>
<td>0.00</td>
<td>2.66</td>
</tr>
<tr>
<td>Predicted Mortality</td>
<td>9,119</td>
<td>0.17</td>
<td>0.17</td>
<td>0.00</td>
<td>0.61</td>
</tr>
</tbody>
</table>

#### Table 3. Discretization

<table>
<thead>
<tr>
<th>State variables</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_t = {0.0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 4.0, \ldots, 10.0, 12.0, \ldots, 30.0}$</td>
<td>29</td>
</tr>
<tr>
<td>$m = {4, 5}$</td>
<td>2</td>
</tr>
<tr>
<td>$Czndv_{it}^{pos}$ (household, 2008-2013)</td>
<td>4</td>
</tr>
<tr>
<td>$\gamma^{nl} = {0, 10000, 20000}$</td>
<td>3</td>
</tr>
<tr>
<td>$\hat{k}_{t-1,t} = {0.0, 2.0, 4.0, 8.0, 12.0, 18.0, 24.0, 30.0}$</td>
<td>8</td>
</tr>
<tr>
<td>$p_{i,t+1}^o = {0, 2000, 4000, 10000, 20000, 40000, 67500}$</td>
<td>7</td>
</tr>
<tr>
<td>total</td>
<td>38,976</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control variables</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_t/k_t = {-0.2, -0.1, 0.0, 0.1, 0.2}$</td>
<td>5</td>
</tr>
<tr>
<td>$\hat{k}_{t,t+1} = {0.0, 2.0, 4.0, 8.0, 12.0, 18.0, 24.0, 30.0}$</td>
<td>8</td>
</tr>
<tr>
<td>total</td>
<td>40</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Other variables</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_t = {0.0, 0.1, 0.2, 0.3}$</td>
<td>4</td>
</tr>
<tr>
<td>$\theta_t = {-0.2, -0.1, 0.0, 0.1, 0.2}$</td>
<td>5</td>
</tr>
</tbody>
</table>

---

15,000 KSH * 30 TLU * (30%−15%)=67,500KSH.
\[ \begin{align*}
\xi_t &= \{0.0, 0.1, 0.2, 0.3\} \\
\hat{m}_t &= \{0.0, 0.1, 0.2, 0.3, 0.4\}
\end{align*} \]

Table 4. Transition Matrix of \( Czdvl_{i, t}^{pos} \) in Maikona from 2001-2013

<table>
<thead>
<tr>
<th>( Czdvl_{i, t}^{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>40</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>-5</td>
<td>29</td>
<td>43</td>
<td>29</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>17</td>
<td>17</td>
<td>33</td>
<td>33</td>
<td>100</td>
</tr>
<tr>
<td>15</td>
<td>0</td>
<td>33</td>
<td>17</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>40</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>100</td>
</tr>
</tbody>
</table>

Note. The number of observations is 1 index area times 25 seasons = 25.

Table 5. Transition Matrix of \( Czdvl_{i, t}^{pos} \) in Lower Marsabit from 2001-2013

<table>
<thead>
<tr>
<th>( Czdvl_{i, t}^{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>33</td>
<td>53</td>
<td>7</td>
<td>7</td>
<td>100</td>
</tr>
<tr>
<td>-5</td>
<td>40</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>28</td>
<td>44</td>
<td>22</td>
<td>100</td>
</tr>
<tr>
<td>15</td>
<td>0</td>
<td>16</td>
<td>26</td>
<td>58</td>
<td>100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>33</td>
<td>53</td>
<td>7</td>
<td>7</td>
<td>100</td>
</tr>
</tbody>
</table>

Note. The number of observations is 3 index areas times 25 seasons = 75.

Table 6. Estimation results: Milk Production Function \( f_{it} \) by \( Czdvl_{i, t}^{pos, it} \geq -10 \) or \( Czdvl_{i, t}^{pos, it} < -10 \)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>( \ln f_{it} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 1{Czdvl_{i, t}^{pos, it} \geq -10} )</td>
<td>0.447***</td>
</tr>
<tr>
<td>( \ln k )</td>
<td>0.340***</td>
</tr>
<tr>
<td>( 1{Czdvl_{i, t}^{pos, it} \geq -10} \times \ln k )</td>
<td>0.085***</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>9.892***</td>
</tr>
</tbody>
</table>

Observations: 6,809
Number of hhid: 982
R-squared: 0.044

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Figure 1. Net Livestock Investment by $Czdvi_{\text{pos,lt}} \geq -10$ or $Czdvi_{\text{pos,lt}} < -10$

Note. The number of observation is 8,564. “1” is the histogram of net livestock investment when $Czdvi_{\text{pos,lt}}^{\text{pos}} \geq -10$. The number of observation of this group is 5,868. “0” is the histogram of net livestock investment when $Czdvi_{\text{pos,lt}}^{\text{pos}} < -10$. The number of observation of this group is 2,696.
Figure 2. Histograms of Predicted Livestock Mortality Index $\hat{m}$ by $C zdv_{i, pos, it} \geq -10$ or $C zdv_{i, pos, it} < -10$ in Maikona index area

The number of observation is 25. “1” is the histogram of $\hat{m}$ with $C zdv_{i, pos, it} \geq -10$. The number of observation of this group is 20. “0” is the histogram of $\hat{m}$ with $C zdv_{i, pos, it} < -10$. The number of observations of this group is 5.

Figure 3. Histograms of Predicted Livestock Mortality Index $\hat{m}$ by $C zdv_{i, pos, it} \geq -10$ or $C zdv_{i, pos, it} < -10$ in Lower Marsabit

The number of observation is 75. “1” is the histogram of $\hat{m}$ with $C zdv_{i, pos, it} \geq -10$. The number of observation of this group is 60. “0” is the histogram of $\hat{m}$ with $C zdv_{i, pos, it} < -10$. The number of observations of this group is
Figure 4. Histograms of Covariate (sub-location-average) Livestock Mortality $\xi_t$ by $Czndvi_{pos,it} \geq -10$ or $Czndvi_{pos,it} < -10$

The number of observation is 160. “1” is the histogram of $\theta_{it}$ with $Czndvi_{pos,it} \geq -10$. The number of observation of this group is 108. “0” is the histogram of $\theta_{it}$ with $Czndvi_{pos,it} < -10$. The number of observation of this group is 52.

Figure 5. Histograms of Idiocyncatic Livestock Mortality Index $\hat{m}$ by $Czndvi_{pos,it} \geq -10$
or $Czdvi_{pos, it} < -10$

The number of observation is 8,564. “1” is the histogram of $\theta_{it}$ with $Czdvi_{pos, it} \geq -10$. The number of observation of this group is 5,868. “0” is the histogram of $\theta_{it}$ with $Czdvi_{pos, it} < -10$. The number of observation of this group is 2,696.

![Histograms of Individual Livestock Birth Rate Shock $b_{it}$ by $Czdvi_{pos, it}$]  

**Figure 6. Histograms of Individual Livestock Birth Rate Shock $b_{it}$ by $Czdvi_{pos, it}$**

Note. The number of observation is 8,564. “1” is the histogram of $b_{it}$ with $Czdvi_{pos, it} \geq -10$. The number of observation of this group is 5,868. “0” is the histogram of $b_{it}$ with $Czdvi_{pos, it} < -10$. The number of observation of this group is 2,696.
Figure 7. Idiosyncratic and covariate livestock mortality ($\theta_i$ and $\xi_i$)

Note. Horizontal axis shows discretized covariate livestock mortality (sub-location average) and vertical axis shows idiosyncratic livestock mortality. Red, green, and orange lines show 25%, 50%, and 75% percentile, respectively.

Figure 8. Predicted and covariate livestock mortality in Lower Marsabit.

Note. Number of observation is 12 sub-locations times 10 seasons = 120. Red, green, orange lines show 25%, 50%, 75% percentile, respectively. Blue line is 45 degree line.
Figure 9. Predicted and covariate livestock mortality in Maikona.

Note. Number of observation is 4 sub-locations times 10 seasons = 40. Red, green, orange lines show 25%, 50%, 75% percentile, respectively. Blue line is 45 degree line.

Figure 10. Milk Production Function $y_i$ by $Czendvi_{pos,lt} \geq -10$ or $Czendvi_{pos,lt} < -10$

The number of observation is 6,809. Blue and red dot are milk production estimates when $Czendvi_{pos,lt} \geq -10$ and $Czendvi_{pos,lt} < -10$, respectively.
Other variables are fixed as follows: $m = 4, Czndvi^{pos}_t = -15.0, \bar{k}_{t-1,t} = 0.0$.

Figure 11. Insured livestock in bad season by non-livestock income in Upper Marsabit

Other variables are fixed as follows: $m = 4, \gamma^{nt} = 0, Czndvi^{pos}_t = -15.0$.

Figure 12. Investment in bad season under autarky and IBLI in Upper Marsabit
Figure 13. Insured livestock by vegetation condition in Upper Marsabit

Other variables are fixed as follows: \( m = 4, y^{nl} = 0, \bar{k}_{t-1,t} = 0.0 \).

Figure 14. Initial asset and last asset under autarky and IBLI by initial asset level and non-livestock income in Upper Marsabit

Other state variables at \( t = 1 \) are fixed as follows: \( m = 4, CZNDVI_{pos1} = 15.0, \bar{k}_{t-1,t} = 0.0, \bar{k}_{t,t+1} = 0.0 \). We simulate asset path 100 times and take median of \( k_{100} \) over 100 simulations. In each simulation, shock variables are set to be the same for autarky and IBLI.