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Preferences for index-based pasture insurance: a choice experiment in Limpopo Province, South Africa

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ABSTRACT

South African subsistence livestock farmers rely heavily on traditional mitigation and coping mechanisms to deal with the effects of drought. However, these methods have proven ineffective in managing the full impact of drought. Consequently, policymakers are increasingly interested in promoting Index-based Pasture Insurance (IBPI). This paper aims to assess subsistence livestock farmers' preferences for IBPI. A simple random sampling method was used to select 110 subsistence livestock farmers for data collection. A discrete choice experiment—Conditional Logit and Latent Class models and incentivized lottery games were used to elicit preferences for insurance contracts and loss aversion. The findings indicate that subsistence livestock farmers have a favourable attitude toward IBPI contracts that protect against drought-related pasture degradation. The Conditional Logit model shows that farmers prefer transparent contracts that reimburse with feed and vouchers rather than cash. However, they derive negative marginal utility from basis risk and premium. However, the Latent Class model reveals heterogeneous preferences for IBPI among farmers. Farmers are also loss-averse, but loss aversion did not influence their preference for IBPI. Therefore, the primary recommendation for insurance providers is to consider customizing IBPI attributes to increase adoption among subsistence farmers.

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1. Introduction

Agriculture is highly susceptible to weather risk, and more than half of the world's population in extreme poverty works in agriculture (Doan et al., 2023). Weather shocks can push vulnerable farmers into poverty traps by forcing them to sell off productive assets (Lybbert et al. 2004) or engage in costly consumption smoothing (Carter and Lybbert 2012). Uninsured risk can also prevent farmers from making profitable investments (Karlan et al. 2014). As a result, innovations that reduce risk in agriculture could play a key role in economic development and poverty reduction. Index insurance offers one such innovation. However, the South African agricultural insurance market is dominated by traditional insurance, i.e., insurance contracts that rely on conventional damage assessment methods and compensate farmers based on actual losses or damages. They usually do not cover livestock risks associated with drought. Insuring pasture is difficult due to its

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low market value, detailed documentation requirements, and a lack of historical data for accurate risk assessment. (Partridge and Wagner 2016). Determining the extent of pasture loss may require on-site evaluations, which can be time-consuming and costly. At the same time, traditional insurance suffers from information asymmetry and high operational costs, limiting widespread adoption among smallholder farming communities (Barnett, Barrett, and Skees 2008).

In attempting to solve this problem, Index-based Pasture Insurance (IBPI) presents a promising alternative solution for insuring against drought-induced deficits in pasture. (Martín-Sotoca et al. 2019). However, due to pending approval from regulators, index-based insurance products are not offered in South Africa (SAIA 2023).

Our latest engagement with the Land and Agricultural Development Bank (LAND BANK) of South Africa revealed that they are in the process of introducing index insurance to provide coverage for crops and livestock against drought. This initiative has received support from the KfW Development Bank and InsuResilience Solutions fund.

The InsuResilience Solutions Fund (ISF) supports the development of innovative climate-risk insurance products implemented in developing and emerging economies to mitigate the effects of climate change. In addition, LAND BANK collaborated with CelsiusPro, an insurance tech group dedicated to helping both private and public institutions understand and mitigate the financial impact of climate change, to design the Area-Yield Index Insurance (AYII) for crops and the Pasture Drought Index Insurance (PDII) for livestock. After submitting these products for regulatory approval, the Prudential Authority provided feedback in November 2020, stating that the products do not currently fit within the insurance regulatory framework as non-life insurance. However, the authority suggested the possibility of regulatory relief to allow for testing and data gathering, facilitating the assessment of functionality and developmental impact under a different classification. Following a consultative meeting between LBIC and the Prudential Authority, it was suggested that LAND BANK seek approval to offer index insurance products in the South African market. As of 2023, LBIC is awaiting approval from the Minister of Finance to start with the pilot.

In this study, we used the term Index-based Pasture Insurance (IBPI) to describe index insurance for livestock. IBPI is an asset protection insurance designed to protect livestock against drought-induced pasture degradation. IBPI relies on the Normalized Difference Vegetation Index (NDVI), an indicator derived from satellite imagery that measures vegetation health at a given pixel (Chantarat et al. 2013; Martín-Sotoca et al. 2019). The index represents calculated NDVI values over time as a proxy for pasture health crucial for livestock feed. The trigger level, or strike level, is a predetermined NDVI value acting as a threshold; if the actual NDVI falls below this during the insured period, it triggers the payout. Payouts are then disbursed to policyholders without the need for proof of individual losses, with the amount linked to the extent of NDVI deviation from the trigger level. The insured period covers summer rainfall (October to March), ensuring optimal monitoring of NDVI during peak vegetation growth. The basis of valuation and sum insured is determined according to the nutritional requirements of insured livestock during the cover period. In this context, the sum insured is based on the supplementary cost of feeding, which is equivalent to one livestock unit.

Indexed-based pasture insurance (IBPI) offers several advantages: transparency, affordability, and quicker payouts. However, IBPI is susceptible to basis risk, which refers to the potential mismatch or imperfect correlation between the index used to determine payouts and the actual losses incurred by the insured party (Keeler and Saitone 2022). Basis risk can result in false negative or false positive outcomes. False negative basis risk occurs when the index used for insurance underestimates the actual losses, leading to a payout that is lower than the losses incurred. False positive basis risk occurs when the index overestimates the actual losses, leading to a higher payout than the losses incurred. There are three types of basis risk: (i) design basis risk, (ii) spatial basis risk, and (iii) temporal basis risk (Dalhaus and Finger 2016). This study focuses on design-based risk, which exists when the index omits some crucial information relevant to predicting losses at the farm level and underestimates the loss. There is growing interest in promoting index insurance products in developing; at the same time, there is low adoption of index-based insurance products across developing countries (Budhathoki et al. 2019; Sibiko, Veettil, and Qaim 2018).

Against this background, this study aims to elicit subsistence livestock farmers' preferences for index-based pasture insurance (IBPI) and determine how loss aversion influences the adoption of IBPI using a discrete choice experiment and Cumulative prospect theory (CPT). As detailed in the next section, we calculated loss aversion using an incentivized lottery game that involved winning or losing a certain amount of money. We then incorporated the loss aversion variable in the DCE model by interacting the loss aversion variable with an alternative specific constant (ASC), which defines two alternatives: choosing IBPI insurance and staying without insurance. This interaction gives valuable information on how loss aversion influences subsistence livestock farmers' propensity to adopt IBP. Our empirical results suggest subsistence livestock farmers are more likely to adopt IBPI if provided with regular information about the index's performance. They also prefer to receive insurance claims in terms of feed and vouchers rather than cash. Moreover, subsistence livestock farmers are sensitive to basis risk. At the same time, farmers with a higher level of education are less susceptible to basis risk, suggesting educated farmers understand the risks associated with IBPI and can make informed decisions about adopting IBPI. However, the influence of loss aversion on the demand for index insurance was not significantly different from zero.

This study builds on a growing body of literature demonstrating how loss aversion influences demand for index-based insurance. These include studies assessing index-based insurance using prospect theory. Lampe and Würtenberger (2020) found that loss aversion negatively affects the uptake of index-based insurance among insurance-illiterate farmers. (Cecchi et al., 2024) studied the impact of loss aversion on willingness to pay for index-based insurance, noting that the loss aversion coefficient changes from negative for conventional insurance to positive for weather-based index insurance. Shin et al. (2022) assessed the demand for index insurance using prospect theory; they showed that insurance demand decreases in loss aversion, and the negative marginal effect of loss aversion on insurance demand increases with basis risk and the insurance premium.

Moreover, this study contributes to the empirical literature on preferences for index-based insurance, precisely how insurance attributes such as premium, basis risk, trigger level, transparency, and payment method influence the willingness to pay. Doherty, Mellett, Norton, McDermott, O'Hora, et al. (2021) found that 69% of farmers favoured insurance against extreme weather, especially weather-index insurance among those concerned about extreme weather. Akter et al. 2016) revealed that high deposit requirements reduced demand for crop index-based insurance (IBI) while increasing bad time and guaranteed payments. Female respondents were more insurance-averse, and trigger levels influenced choices only in the insurance-favorable group. Sibiko, Veettil, and Qaim (2018) showed that Kenyan smallholder farmers preferred insurance with early payouts, regular weather data communication, shorter distances to weather stations, and group insurance. Farmers were willing to pay a higher percentage of their expected harvest for these preferred contract attributes. Doherty, Mellett, Norton, McDermott, Hora, et al. (2021) choice experiment study shows that most farmers are willing to buy subsidised insurance, especially younger farmers, those with existing insurance, and those in previously affected regions.

However, many studies overlook crucial behavioural aspects and index insurance attributes such as basis risks and trigger levels. These limitations can lead to inadequate product design that fails to consider the heterogeneity of farmer risk profiles, ultimately resulting in lower demand (Ceballos and Robles 2020). To our knowledge, we are the first to incorporate loss aversion in a choice experiment. Our approach differs from that of the abovementioned studies. In this case, we have applied four assumptions regarding probability weighting and diminishing sensitivity. The first assumption is that probability weighting and diminishing sensitivity are unimportant. The second assumption is that probability weighting affects loss aversion; however, diminishing sensitivity does not. The third assumption is that probability weighting does not impact loss aversion, but diminishing sensitivity does. The fourth assumption is that probability weighting and diminishing sensitivity impact loss aversion. We calculated each assumption's sample mean and median loss aversion coefficients. We test the influence of loss aversion in the choice experiment.

2. Methodology

2.1 Elicitation of loss aversion

Farmers' loss aversion was elicited using lottery games adapted from Gächter, Johnson, and Herrmann (2022)

However, this current study used balls instead of dice to make the game easier and accommodate respondents with low literacy levels. This design effectively elicits loss aversion under cumulative prospect theory (CPT). The lottery game entails six (6) choice lottery tasks that involve a 50% chance of winning and a 50% chance of losing a certain amount of money. Before the experimentation began, respondents were incentivized with 25 ZAR (1.56 USD)–the equivalent of the South African minimum hourly wage for participation and avoided net losses from playing a lottery game. In this lottery task experiment, losses varied from 8 ZAR (0.5 USD) to 23 ZAR (1.44 USD), while gains remained constant at 20 ZAR (1.25 USD). Then, respondents were required to decide whether they wanted to accept or reject some or all of the six lotteries, which means they wanted to play or reject the game. If they reject all lotteries, they only gain an incentivized value of 25 (1.56 USD) ZAR to avoid net loss. A list of lottery tasks presented to the respondents is shown in Table 1.

After completing the lottery task, the enumerator inserted numbered balls into a bag. These numbered balls represented the lotteries that the respondents had accepted. Then, randomly drew a numbered ball from the same bag, determining the row the respondent will play for real money. For example, if one draws ball number two, the respondent will play row two (2) for real money. In the best situation for respondents, when the lottery outcome was positive, the enumerator would pay them 25 ZAR (1.56 USD) as participation compensation plus 20 ZAR (1.25 USD) that they earn by winning a game. In the worst-case situation, where the respondent loses, the enumerator had to deduct the losses from the initial payment the respondent received as an incentive.

2.2 Eliciting preferences for insurance attributes

2.2.1 Discrete choice experiment

In a DCE, respondents are presented with scenarios, each describing choices characterised by varying levels of specific attributes. Participants are then asked to choose their preferred alternative from each scenario. The experiment design and analysis of the choice outcomes are rooted in the random utility theory (RUT) (McFadden 1986). Individuals are assumed to choose based on the utility they derive from each alternative. This utility comprises a systematic component (a function of observable attributes of the other options) and a random component to account for unobservable

Table 1. Illustration of lottery game matrix.

	Lottery	Accept	Reject
L1	If the coin turns up heads, the respondent loses 8 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		
L2	If the coin turns up heads, the respondent wins 11 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		
L3	If the coin turns up heads, the respondent loses 14 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		
L4	If the coin turns up heads, the respondent loses 17 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		
L5	If the coin turns up heads, the respondent loses 20 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		
L6	If the coin turns up heads, the respondent loses 23 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		

Table 2. Attributes and levels.

Attributes	Descriptions	Levels
Transparency	Information about an index's performance. Weekly updates provide SMS updates on pasture degradation, influencing insurance payout.	Receive Weekly Updates, No Weekly Updates
Premium to pay	Premium amounts are based on the insurance contract.	100 ZAR, 250 ZAR, 400 ZAR
Reimbursement method	Options for receiving insurance claims. Voucher: redeemable for feed and services; Cash: direct bank deposit; Feed: delivery of supplementary feed.	Voucher, Cash, Feed
Basis risk	Possibility of false negative basis risk in index-based insurance. Ranges from 8 to 16 out of 100 times.	1 out of 10 times, 2 out of

factors. The relative utilities of the available options then determine the probability of choosing a particular alternative. Critical stages in the implementation of a DCE include the identification and definition of attributes (and the possible levels), the experimental design to create choice scenarios, and the analysis of collected data using statistical models.

2.2.2 Selection of attributes

The attributes and levels of the IBPI to be presented to farmers were chosen through a comprehensive literature review, two online focus group discussions with livestock farmers, and consultations with various experts. The expert panel included representatives from insurance companies, government officials, academics, farmers' organisations, and the Johannesburg Stock Exchange. A refined set of attributes and corresponding levels emerged after synthesising insights from the literature review, focus group discussions, and expert consultations (Table 2).

2.2.3 Experimental design

Prior information about South African livestock farmers' preference for these attributes was unavailable. Thus, we conducted a pilot study involving 20 substance livestock farmers to test the attributes and levels and obtain priors for constructing an efficient design. In this first step, we used the Ngene software to create an orthogonal design consisting of 18 choice sets, each having two IBPI alternatives plus an opt-out alternative. We split this design into blocks of nine choice sets to reduce the cognitive burden. We found that the respondents understood the choice experiment exercise in the pilot study. However, they perceived that the number of choice sets was excessive.

Based on the information obtained from this first survey round, we constructed a D-Efficient design with two unlabelled IBPI alternatives and one opt-out alternative (no insurance purchased). To avoid respondent fatigue, the choice sets were split into two blocks, each containing six choice sets. The opt-out alternative was included to prevent the forced purchase of insurance that could lead to contradictions and inconsistencies with the demand theory. Each choice card was accompanied by a reminder of how IBPI payment is triggered, as shown in Table 2. We presented six choice cards with three alternatives to farmers, resulting in 1,818 alternatives, with 93% representing IBPI and 7% representing "no insurance." (Table 3)

Table 3. An example of a choice card.

	Contract A	Contract B	Option C
Reimbursement method	Feed	Cash	Stay without insurance
Transparency	No Weekly Updates	Receive Weekly Updates	
Basis Risk	8 out of 100 times	12 out of 100 times	
Premium to pay	250 ZAR	100 ZAR	

The remainder of trigger levels and their expected compensation											
Pasture degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	0	0	2500	2917	3333	3750	4167	4583	5000	5000

2.3 Data collection

The data collection process for our study consisted of two phases: survey piloting for pretesting and the final data survey implementation. Both phases were carried out in the Makhado local municipality, Limpopo Province, South Africa, between March and July 2021. For the pilot survey, we randomly selected 20 respondents. For the final survey, we randomly selected 110 farmers. The interviews were organised into five sessions: background and discussion about insurance, choice experiment, self-reported risk tolerance, lottery game, and sociodemographic questions. We included debriefing questions to assess how the respondents made their choices and their level of understanding.

Additionally, we asked an open-ended question about the maximum WTP for the IBPI contract, the difficulty of making a choice, and the strategies used when making a choice. Regarding loss aversion, we asked farmers to play an incentive lottery game that involved winning or losing a certain amount. Finally, in the sociodemographic section, we collected data on subsistence farmers' socioeconomic characteristics, exposure to drought risk, drought management strategies, and access to weather information.

2.4 Data analysis

2.4.1 Loss aversion

Loss aversion was elicited using data from lottery tasks using cumulative prospect theory (Tversky and Kahneman 1992). If a decision maker is presented with a lottery task, he or she will be indifferent between accepting or rejecting it if:

$$w^{+}(0.5)v(G) = w^{-}(0.5)\lambda^{risk}v(L) \tag{1}$$

where L represents the losses, G represents the gains in each lottery, $v(x)$ is the utility of outcome (either gains or losses), λ^{risk} represents the loss aversion coefficient in the risky lottery and $w^{+}(0.5)$ and $w^{-}(0.5)$ represent the probability weights for the 50% probability of losses and gains in the lottery game (Gächter, Johnson, and Herrmann 2022).

From equation (1), we get:

$$\lambda^{risk} = \frac{w^{+}(0.5)v(G)}{w^{-}(0.5)v(L)} \tag{2}$$

If we assume that $w^{+}(0.5) = w^{-}(0.5)$, and a linear utility function ($v(x) = x$), then we get $\lambda = \frac{G}{L}$, which denotes implied loss aversion in the lottery choice task. Therefore, we tested four scenarios regarding the ratio of probability weights $w = \frac{w^{+}(0.5)}{w^{-}(0.5)}$, and the curvature of the utility function characterised by α and β in a power utility function, where v is defined by $v(G) = G^{\alpha}$, $v(L) = G^{\beta}$.

In this case, we have applied four assumptions regarding probability weighting and diminishing sensitivity. The first assumption is that probability weighting and diminishing sensitivity are unimportant, meaning that $w = 1$ and $\alpha = \beta = 1$. The second assumption is that probability weighting affects loss aversion ($w \neq 1$); however, diminishing sensitivity does not ($\alpha = \beta = 1$). We used the probability weighting estimates, $w^{+}(0.5) = 0.394$ and $w^{-}(0.5) = 0.456$, i.e., $w = 0.864$ from the study by Abdellaoui (2000). The third assumption is that probability weighting does not impact loss aversion ($w = 1$) but diminishes sensitivity does. We used diminishing sensitivity estimates (i.e., $\alpha = 0.72$ and $\beta = 0.73$) from the survey by Abdellaoui, Bleichrodt, and Paraschiv (2007). The fourth assumption is that probability weighting and diminishing sensitivity impact loss aversion. We calculated each assumption's sample mean and median loss aversion coefficients.

2.4.2 Discrete choice experiment

Our primary models are the conditional logit and the latent class models. They derive from the random utility theory, which posits that the utility that individual *n* derives from alternative *i* in the choice set t, U_{njt}, can be decomposed into a deterministic component V_{njt} and a random component ε_{njt}. The observable component is assumed to be a linear function of the attribute levels:

$$U_{nit} = V_{nit} + \varepsilon_{nit} = ASC_i + X'_{nit}\beta + \varepsilon_{nit}, \tag{3}$$

where X_{nit} is a vector containing all the attributes of the good to be evaluated, β is the vector of the corresponding parameters, and ASC_i is the alternative specific constant. Since we have an unlabelled experiment, ASC_i is set to zero when i is not the opt-out alternative. Therefore, ASC will represent the utility of the opt-out option, i.e., of not choosing alternative either A or B. Assuming that the random part of utility is extreme value type 1 distributed with location parameter zero and scale parameter one, it was shown that the probability of individual n choosing alternative i in the choice set t is:

$$P_{nit} = \frac{\exp(ASC_i + X'_{nit}\beta)}{\sum_{j=1}^{J}\exp(ASC_j + X'_{njt}\beta)} \tag{4}$$

With these assumptions, we can estimate the parameters β that maximise the log-likelihood function (Louvière et al., 2000):

$$LLik(ASC, \beta) = \sum_{n=1}^{N}\sum_{j=1}^{J} y_{njt}\log(P_{njt}) \tag{5}$$

where y_{njt} is an indicator variable taking the value one when individual n chose the alternative j in the choice situation t, and zero if she chose another alternative.

The latent class model extends the conditional logit model by incorporating latent (unobservable) classes with their distinct choice behaviour, i.e., their distinct β parameters. While the conditional logit model assumes homogeneity in individual preferences across the entire population, different models have been developed to analyse the heterogeneity of preferences within the population. The two most popular are the random parameter (or mixed) logit model and the latent class logit model. The two models differ in how they represent this heterogeneity. In the random parameter logit model, coefficients vary across individuals and follow a continuous distribution. The model achieves this by introducing random coefficients drawn from a continuous probability distribution, reflecting the variability in tastes among the population. Conversely, the latent class logit model assumes that the population can be partitioned into distinct, unobservable (latent) classes, each characterised by a unique set of preference coefficients. It assumes a discrete distribution of parameters.

Individuals within the same latent class share common preferences, and the model calculates the preference coefficients and the probability of an individual belonging to each class. The socio-demographic characteristics of the respondents can influence these probabilities. Both models contribute to understanding the sources of preference heterogeneity within a population, but we chose the latent class formulation as it provides a more intuitive interpretation to decision-makers. Following Greene and Hensher (2003), it can be shown that the log-likelihood function to estimate a latent class logit model is

$$logLik(\beta_c) = \sum_{n=1}^{N} ln\left[\sum_{c=1}^{C}\frac{\exp(Z'_n\theta_c)}{\sum_{c'=1}^{C}\exp(Z'_n\theta_{c'})}\left(\prod_{t=1}^{T_n}\frac{\exp(X'_{nit}\beta_c)}{\sum_{j=1}^{J}\exp(X'_{njt}\beta_c)}\right)\right]. \tag{6}$$

Where β_c is the class-specific parameter, and Zn is a vector of socio-demographic parameters influencing the probability of a respondent belonging to the different latent classes. The number of classes cannot be known beforehand or estimated simultaneously with the other parameters. Estimating the same LCM with varying numbers of classes is common practice. The number of classes is chosen using information criterion (AIC and BIC) and the plausibility of the classes obtained. Following the above-described choices experiment framework, we used attributes presented in Table 2 to mathematically capture preferences for IBPI to test our hypothesis as follows:

$$\begin{aligned} V_{nit} = {} & ASC_{nit+}\ ASC_{nit}(LS_{ijt} + TL_{ijt} + DF_{ijt} + AL_{ijt} + WF_{ijt}) \\ & + \beta_1 Transparency_{nit} + \beta_2\ Voucher_{nit} + \beta_3\ Feed_{nit} + \beta_4\ BasisRisk_{nit} \\ & + \beta_7\ (BasisRisknit^{*}Educ_{ijt}) + \beta_8\ \ Premium_{nit} + \beta_9\ \ (Premium^{*}_{nit}Educ_{ijt}) + \ \varepsilon_{nit} \end{aligned} \tag{7}$$

tributes described in Table 2 are used to model the utility function of the IBPI. The Alternative Specific Constant (ASC) represents the non-insurance option and is a reference. The interaction effects are examined by the interaction of ASC with loss aversion (LS), trigger level (TL), drought frequency (DF), arable land size (AL), and weather forecast (WF). These interactions help us understand how these variables influence the utility of insurance alternatives. Moreover, this study examines the effects of interaction between education, basis risk (likelihood of false negatives), and premium attributes. The rationale lies in these factors' diverse impact on individuals with varying educational backgrounds. Farmers with different education levels may interpret these aspects differently and respond to them in contrasting ways. Transparency is modelled as a dummy variable with a value of one representing receiving weekly updates regarding index performance. At the same time, the reimbursement method is the option of using vouchers and feeds to receive an insurance payout, which is coded as dummy variables compared with cash as the base level. Basis risk is a continuous variable attribute representing the likelihood of false negatives, with levels indicating varying frequencies of this risk. Premium represents the monetary amount farmers will pay. Regarding the latent class model, attributes in Table 2 also explain the utility function in different classes. The structural equation for the latent class is as follows.

$$\begin{aligned} V_{nit} = {} & ASC_{cnit} + \beta_{c,2}Transparency_{nit} + \beta_{c,3}\ Voucher_{nit} + \beta_{c,4}\ Feed_{nit} + \beta_{c,5}\ BasisRisk_{nit} \\ & + \beta_{c,6}\ Premium_{nit} + \varepsilon_{nit} \end{aligned} \tag{8}$$

The allocation probability that determines the likelihood that an individual belongs to a specific latent class is estimated as follows:

$$\Psi_{nc} = \frac{\exp(\gamma_0 + \gamma_{1c}AL + \gamma_{2c}WF + \gamma_{3c}YF + \gamma_{4c}DF + \gamma_{4c}LA)}{\sum_{c=1}^{C}\exp(\gamma_0 + \gamma_{1c}AL + \gamma_{2c}WF + \gamma_{3c}YF + \gamma_{4c}DF + \gamma_{4c}LA)} \tag{9}$$

where n represents an individual, while c represents the latent class, with C being the total number of latent classes, the allocation probability, denoted as Ψnc, signifies the likelihood of individual n belonging to latent class c. The parameter γ_0 is the intercept or baseline for the latent class model, and γ_{1-4c} are associated with specific variables: arable land (AL), WF (Weather forecast), Young Farmers (YF), Drought Frequency (DF) and Loss Aversion of individual n. Parameters γ_0 and γ_{1-4c} are normalised to zero to secure identification of the model. Regarding the willingness to pay, the standard consumers' theory suggests that the marginal rate of substitution (MRS) can be computed by taking a partial derivative of (2.1) concerning non-monetary and monetary attributes. Typically, the MRS is interpreted as the Willingness to Pay (WTP), which can be computed by taking the ratio of non-monetary and monetary attribute coefficients specified in (3) as follows:

$$MRS_{trasnparency} = -\frac{\beta_1 Transparency_{nit}}{\beta_8\ \ Premium_{nit}} \tag{10}$$

$$MRS_{Voucher} = -\frac{\beta_2\ Voucher_{nit}}{\beta_8\ \ Premium_{nit}} \tag{11}$$

$$MRS_{Feed} == -\frac{\beta_3 Feed}{\beta_8\ \ Premium_{nit}} \tag{12}$$

$$MRS_{Basis\ Risk} = -\frac{\beta_4\ BasisRisk_{nit}}{\beta_8\ Premium_{nit}} \tag{13}$$

$$MU_{BasisRisk} = \frac{\partial V_{nit}}{\partial BasisRisk_{nit}} = \beta_4\ + \beta_7\ (Educ_{ijt}) \tag{14}$$

$$MU_{Premium} = \frac{\partial V_{nit}}{\partial BasisRisk_{nit}} = \beta_8\ + \beta_9\ (Educ_{ijt}) \tag{15}$$

$$MRS_{Basis\ Risk} = -\frac{MU_{BasisRisk}}{MU_{Premium}} = -\frac{\beta_4\ + \beta_7\ (Educ_{ijt})}{\beta_8\ + \beta_9\ (Educ_{ijt})} \tag{16}$$

The CL model was used to determine willingness to pay for a product feature by analysing the coefficients assigned to different attributes. These coefficients signify the impact of attribute changes on the odds of selecting an alternative over others. The magnitude and sign of the coefficients provide valuable insights into the significance and direction of influence of each attribute on the decision-making process. By comparing the coefficient ratio of a specific attribute to that of the premium attribute, we can measure the trade-off farmers are willing to pay for a particular attribute.

3. Results

3.1 Descriptive statistics

This study surveyed 110 farmers, predominantly male (61%) and female (39%) respondents, to assess the importance of education in understanding insurance products. The findings indicate that 39% of farmers lack formal education, highlighting the need for targeted communication. Despite engaging in subsistence farming, the respondents face numerous challenges, such as recurring droughts, resulting in an average of six livestock mortalities. Moreover, issues such as limited access to private land and overgrazing exacerbate farmers' challenges, with the average arable land per farmer being 2.77 hectares. The annual average income from livestock farming is 75 259.41 (5 017.29 USD), supplemented by government grants for 46% of the respondents. The study also found that accessing formal credit is challenging for subsistence farmers, with only 33% having access (Table 4).

Table 4. Sample.

Statistic	Description	Mean	S.e
Age	Number of years	56.28	14.78
No education	Dummy	0.39	0.46
Primary education	Dummy	0.24	0.43
Secondary education	Dummy	0.40	0.49
Tertiary education	Dummy	0.07	0.26
Herd size	Number of livestock	18.35	14.25
Arable land	Hectares	2.77	2.57
Household size	Number of households	5.44	1.95
Male	Dummy	0.61	0.49
Female	Dummy	0.39	0.49
Drought in the past five years	Number of years	2.39	1.15
Drought-related livestock mortality	Number of livestock mortality	5.66	7.67
Access to formal credit	Dummy	0.33	0.47
Social grant beneficiaries	Number of efficacies	0.46	0.50
Number of years in farming	Number of years	11.89	7.91
Income	ZAR (US dollars)	75,259.41 (5,017.29)	60,087.07 (4005.80)
Number of respondents	110		

Table 5. Loss aversion parameters.

Lottery Task	Acceptable loss	(a) λ_1	(b) λ_2	(c) λ_3	(d) λ_4	Frequency
Assumptions		w=1 α=1 β=1	w=0.864 α=1 β=1	ω=1 α=0.72 β=0.73	ω=0.864 α=0.72 β=0.73	
1. Reject all lotteries	<8 ZAR	>2.5	>2.16	>1,89	>1,64	18 (16%)
2. Accept_L1, reject L2 to L6	8 ZAR	2.50	2,16	1,89	1,64	15 (14%)
3. Accept_L2, reject L3 to L6	11 ZAR	1.81	1,57	1,50	1,30	25 (23%)
4. Accept_L3, reject L3 to L6	14 ZAR	1.43	1,24	1,26	1,09	30 (27%)
5. Accept_L4, reject L4 to L6	17 ZAR	1.18	1,02	1,09	0,94	18 (16%)
6. Accept_L5, reject L6	20 ZAR	1.00	0,86	0,97	0,84	4 (4.0%)
7. Accept all lotteries	23 ZAR	≤0.86	≤0,75	≤0,88	≤0,76	0 (0.0%)
	Median (L2)	1.81	1.57	1.500	1.30	
	Interquartile range (L3-L1)	1.43–2.5	1.24–2.16	1.26–1.89	1.09–1.64	

(a) Benchmark parameters: no probability weighting and no diminishing sensitivity; (b) No probability weighting but diminishing sensitivity; (c) Probability weighting, but no diminishing sensitivity; (d) Probability weighting and diminishing sensitivity.

3.2 Loss aversion

Table 5 presents loss aversion results. 96% of farmers accepted lottery tasks with strictly positive expected values, indicating loss aversion. Only 4% of farmers accepted a lottery task with zero expected values (G = L), suggesting they are not loss averse. No farmers accepted lotteries, implying a loss (L6). On the other hand, a substantial number of farmers rejected all lotteries ($\lambda_1 > 2.5$), suggesting the sample included an essential proportion of strongly loss-averse farmers. The median respondent's cutoff lottery was L4: they accepted lotteries L1 and L2 but rejected lotteries L3 to L6, which in the benchmark assumption implies $\lambda_1 = 1.81$.

The median values of all the loss aversion parameters ($\lambda_{1\text{-}4}$) were higher than one, meaning farmers exhibit loss aversion across all four assumptions. Moreover, all loss aversion parameters

Table 6. Conditional model estimates.

	Model 1		Model 2	
Variables	Coefficient	s.e.	Coefficient	s.e.
ASC	−1.26***	0.32	0.24	0.91
Transparency	0.33***	0.09	0.33***	0.09
Reimbursement method				
Voucher	0.18	0.13	0.18	0.12
Feed	0.77***	0.13	0.77***	0.13
Basis risk	−0.46*	0.28	−0.52*	0.29
Basis Risk x Education	0.25*	0.10	0.27**	0.10
Premium	−0.21*	0.09	−0.22*	0.09
Premium x Education	0.01**	0.04	0.10**	0.04
ASC x Size of arable land (hectares)	–	–	−0.26 **	0.09
ASC x Drought Frequency	–	–	−0.29 *	0.14
ASC x Loss aversion (λ_4)	–	–	−0.13	0.32
ASC x Trigger level 2 _loss	–	–	−0.25	0.34
ASC X Weather forecast	–	–	0.13	0.32
Model statistics				
AIC	1049.21		670.09	
BIC	1084.47		615.92	
Rho-square	0.22		0.24	
Final log-likelihood	−516.61		−509.19	
Number of individuals	101		101	

Signif. Codes ***, **, and * indicate significance at 1%, 5%, and 10% levels, and s.e stands for standard error.

were skewed to the right and concentrated on the range λ>1, indicative of loss aversion (as opposed to loss tolerance, where λ<1). The study's reported range of loss aversion falls within the range reported by other studies that assumed probability weighting and diminishing sensitivity. (Booij, Van Praag, and Van De Kuilen 2010).

3.3 The conditional logit model estimates

The results of the conditional logit models are presented in Table 6. The models' statistics, such as AIC, BIC, log-likelihood, and pseudo-R square, suggest that both models are highly appropriate for the dataset, indicating that the attributes and levels of the models are informative and contribute to accurately estimating farmers' preferences for IBPI.

Both models present expected and unexpected results. In the first model, most attributes were significant and conformed to theoretical expectations. The ASC coefficient was negative and significant, suggesting respondents had a positive attitude towards IBPI. In addition, the important and positive coefficient for transparency shows a favourable preference for receiving weekly updates about index measurements, indicating that information transparency and frequent communication regarding index performance can strengthen farmers' confidence in IBPI.

The voucher had a positive coefficient that conforms to theoretical expectations. However, it was not significantly different from zero, suggesting that farmers did not perceive vouchers as an essential attribute. At the same time, the mean coefficient of feed is positive and significant at a 1% level, suggesting that farmers derived positive marginal utility from the IBPI contracts that reimburse in terms of feed compared with cash. We expected this outcome because the DCE debriefing survey suggests that most farmers confirmed that they paid more attention to feed as a mode of payment when making their choices. However, few respondents mentioned cash as their preferred reimbursement mode. The motivation for farmers' low preference for cash as a mode of reimbursement is the eagerness to circumvent the possible deviation of spending the insurance payout on the intended purposes.

Moreover, farmers want to leverage convenience in purchasing feed since the transaction cost of procuring feed is high because they reside in remote areas with limited access to roads and means of transportation. As expected, basis risk gives farmers disutility because it puts them at risk of receiving low insurance reimbursement relative to losses incurred; the coefficient is negative and significant at a 10% level. Conversely, farmers with an additional level of education deviated from the theoretical expectation because basis risk does not decrease their likelihood of purchasing insurance. The negative overall interaction effect between basis risk and education is −0.21936, suggesting that the presence of education moderates the negative impact of basis risk on the utility. This could imply that individuals with higher education levels may be more resilient or less adversely affected by changes in basis risk compared to those with lower education levels. This will be tested when calculating willingness to pay. Jensen, Mude, and Barrett (2018) tested the impact of Index-based Livestock Insurance (IBLI) knowledge on the demand response to basis risk by interacting basis risks with an indicator variable representing participation in a randomised educational game. They find that increased IBLI knowledge through involvement in randomised education games significantly increased negative sensitivity to basis risk. There was a minimal relationship between basis risk and demand among those who did not participate in educational games. The leading coefficient of farmers' preference regarding premiums is negative and significant, which conforms to the theoretical expectation that farmers derive disutility from premiums. The interaction coefficient is positive and significant; this suggests that farmers with one more education level have a preference coefficient of −0.19 (−0.21 + 0.013). Therefore, they have lower negative marginal utility for money than less educated farmers. Since the absolute value of the marginal utility decreases with education, the WTP for the premium attributes increases with education.

Regarding the second model, the introduction of interaction parameters with the ASC did not change the magnitude and significance of the parameters of the first model. The first interaction is between ASC and the loss aversion parameter (λ_4), which simultaneously assumes probability weighting and diminishing sensitivity. The reason for using the latter loss aversion parameter is due to the low standard deviation, which has the potential to produce reliable statistical inferences. The negative coefficient suggests that loss-averse farmers are more willing to take up IBPI contracts. However, the coefficient is not statistically different from zero, indicating that loss aversion does not influence the uptake of IBPI.

Furthermore, the results do not improve when ASC interacts with other loss aversion parameters. Conversely, Hwang (2021) found that loss aversion substantially reduces the likelihood of taking health insurance. In contrast, a study conducted in South Africa in the context of small-scale farmers showed that the higher the loss aversion, the greater the likelihood of taking up technology bundled with insurance (Visser, Jumare, and Brick 2020). The interaction between ASC and drought frequency is negative and significant at 10%. This coefficient suggests that farmers vulnerable to drought are more likely to adopt IBPI to improve their status quo. Similar results were reported by Castellani, Vigan, and Tamre (2014), who showed that farmers who experienced lower frequency drought are less likely to purchase index insurance. These findings indicate that farmers are aware of their risk exposure and are willing to take necessary steps to mitigate it. When ASC interacted with the trigger level, the coefficient was negative and insignificant, suggesting that trigger levels did not influence preferences for IBPI. This result contradicts what was reported by Sibiko, Veettil, and Qaim (2018), who observed significant heterogeneity concerning trigger levels. Some farmers prefer IBPI contracts with lower trigger levels because they reimburse them early before they experience severe damage.

Akter et al. (2016) Found that insurance-averse farmers prefer index-based insurance associated with lower trigger levels since it covers the high risk of rainfall deficiency. Simultaneously, in a segment with farmers favouring insurance, they observed that trigger levels did not significantly influence insurance choice. Regarding weather forecasts, the theoretical expectation is that farmers tend to adjust the demand for insurance according to the anticipated weather conditions in the upcoming season. The results show that having access to weather forecast information about El Niño, La Niña, and other weather conditions does not significantly influence the WTP for IBPI. In comparison, Jensen, Mude, and Barrett (2018) found that farmers with access to information revealing bad rangeland conditions had a high likelihood of purchasing insurance. Furthermore, the interaction between ASC and the size of arable land is negative and significant, indicating that farmers with large land sizes are likely to take up insurance contracts.

3.4 Willingness to pay for IBPI

Conditional logit estimates were used to analyse the willingness to pay for IBPI attributes, which shed light on farmers' distinct priorities and preferences. Figure 1 shows the WTP estimate for IBPI attributes, where WTP_BR0, WTP_BR1, WTP_BR2, and WTP_BR3 values represent the willingness to pay for basis risks at no formal, primary, secondary, and tertiary education levels, respectively. WTP_feed, WTP-Trans, and WTP_Voucher present willingness to pay for feed, transparency, and voucher attributes. Farmers without formal education are willing to pay R220.1455 less for contracts with basis risk. This implies that the additional satisfaction or value gained from avoiding basis risk is worth R220.1455 for farmers with no formal education.

Similarly, farmers with primary and secondary education levels are willing to pay R152.59 and R351.64 less, respectively, indicating their decreasing marginal utility for avoiding basis risk. Farmers with tertiary education have the highest reduction in WTP, willing to pay R550.69 less for contracts with basis risk. This suggests that, on average, farmers with higher education levels place a lower value on avoiding basis risk, indicating a diminishing marginal utility as education level increases.

On average, farmers are prepared to pay an additional R155.5146 for every unit increase in the transparency of insurance policies. The positive value denotes a positive marginal utility, implying

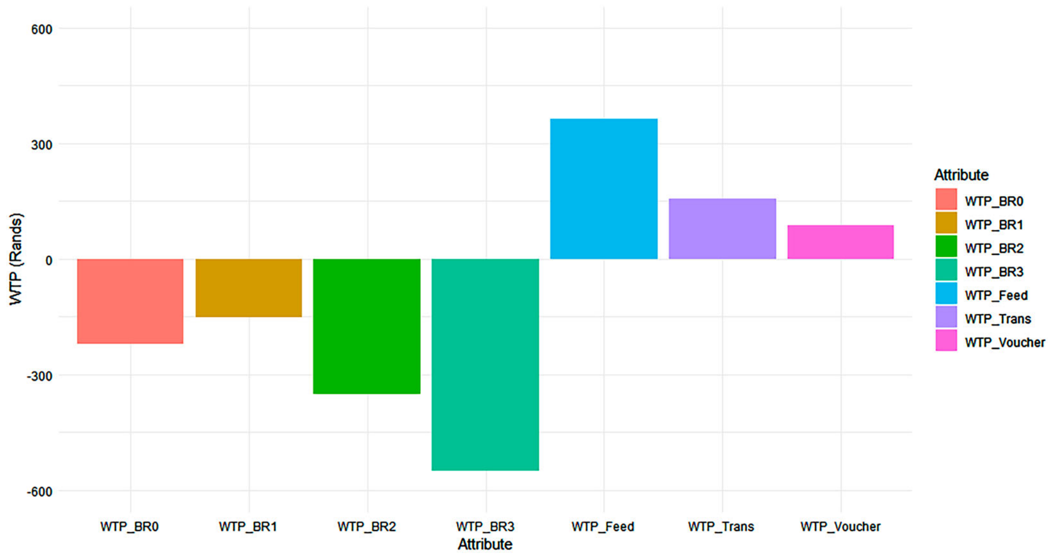

Figure 1. Willingness to pay estimates for index-based pasture insurance.

that incremental transparency enhancements result in a notable rise in utility derived from transparency. Individuals are willing to pay R362.6189 for every unit improvement payout using the feed. The positive WTP value for vouchers is R86.6191, which indicates that individuals are willing to pay this sum for each additional unit of voucher-related attributes in the insurance product. This positive marginal utility suggests that the inclusion or enhancement of vouchers acts as an appealing incentive for policyholders.

3.5 The latent class (LC) model

We estimated three LC models containing two to four classes, searching for an optional number of classes to keep. Table 7 shows the model fit statistics. The model fit statistics entails AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and LL (Log-Likelihood) across two to four classes of models. The BIC is minimum in the two-class model, suggesting that adding more classes does not improve model fit. As classes increase, AIC decreases. However, the marginal change of AIC beyond two classes is significantly small, suggesting that adding more classes beyond two classes does not generate a statistical improvement in the model. Therefore, jointly considering the above criteria, the two-class model was retained. Another reason to prefer the two-class model over other models is that the utility coefficients in the two-class model are more interpretable than in other models. Since the LC model is an extension of the conditional logit model, comparing AIC and BIC in the two models reveals that the LC model is an improvement over the CL model.

The results for the two-class LC model are in Table 8. LC estimates show heterogeneous preferences for IBP attributes. Here, farmers had a 53% probability of belonging to the first class and a 47%

Table 7. The latent class model selection criteria.

	Class 2	Class 3	Class 4
AIC	1029.92	1024.60	1023.61
BIC	1109.25	1156.80	1208.70
LL	−496.96	−482.30	−469.81
Number of parameters	18	30	42
Sample Size	101	101	101

probability of belonging to the second class. Regarding the class membership probability model, the socioeconomic characteristics of farmers did not significantly influence the likelihood of belonging to a particular class, except for livestock sales. This outcome suggests that farmers who sold one additional livestock unit in the previous year are likelier to belong to the second class than those who sold more miniature livestock. Jensen, Mude, and Barrett (2018) found no clear and robust relationship between index insurance and socioeconomic characteristics (e.g., age, assets, wealth, education, gender, household head, and herd size). The ASC across two classes has a negative and significant coefficient at a 1% level, suggesting that farmers in both classes have a positive attitude towards IBPI. The essential attributes in the first and second classes conform to theoretical expectations and are significant, yet some deviate.

The transparency attribute conforms to theoretical expectations regarding the first class since the coefficient is positive and significant at the 1% level. This outcome suggests that farmers categorised as first-class prefer IBPI contracts that provide weather information through a weekly SMS detailing the index's performance. In the reimbursement method, the mean coefficient of the voucher is negative and insignificant, suggesting that farmers in this class do not perceive vouchers as an essential mode of reimbursement compared to the cash option. At the same time, the mean coefficient of feed is positive and significant at a 1% level, suggesting that farmers perceive feed as an essential mode of reimbursement compared to cash. Furthermore, the mean coefficient of basis risk is positive and significant at the 5% level, which deviates from the theoretical expectation that farmers derive disutility from basis risk. This deviation can be attributed to misunderstanding the basis risk concept and its implications, requiring further research to find an appropriate way to express basis risk. Finally, the premium attribute coefficient is positive and significant at a 5% level, deviating from the theoretical expectation that farmers derive negative marginal utility.

In the second class, the transparency attribute is negative and significant at the 10% level, deviating from the theoretical expectation that farmers will prefer index insurance contracts that are more transparent. Concerning the reimbursement method, the mean coefficient of voucher and feed are positive and significant at 10% and 1%, respectively. This result shows that farmers in the second class derive a positive marginal utility from the IBPI contract that reimburses the insurance claim

Table 8. Latent class model estimates.

	Class 1		Class 2	
Variables	Estimate	s.e.	Estimate	s.e.
ASC	−1.98***	0.43	−1.98***	0.43
Transparency	0.86***	0.25	−0.35*	0.18
Voucher	−0.13	0.145	0.27**	0.18
Feed	0.64***	0.22	1.10***	0.28
Basis risk	0.59**	0.27	−0.57*	0.30
Premium	0.16**	0.08	−0.30***	0.09
Class probability model				
Livestock sales	−0.26*	0.13	–	–
Size of arable land	0.17	0.18	–	–
Weather forecast	0.91	0.55	–	–
Young farmers	1.08	0.69	–	–
Drought Frequency	−0.17	0.24	–	–
Loss Aversion	0.72	0.85	–	–
Education	−0.26	0.37	–	–
Model statistics				
Segment probability	0.53		0.47	
AIC	1029.89		–	
BIC	1109.21		–	
Rho–square	0.2536		–	
LL (0, whole model)	−665.76		–	
LL (final, whole model)	−496.94		–	
N	101			

Signif. Codes ***, **, and * indicate significance at 1%, 5%, and 10% levels, where s.e standards for standard error.

in vouchers and feeds instead of cash. Regarding the basis risk, as expected, the mean coefficient is negative and significant at a 10% level, suggesting that the farmers categorised in the second class prefer IBPI contracts with a lower basis risk. Finally, the premium attribute is negative and significant at a 1% level, showing that the farmers prefer IBPI contracts with a lower premium as they derive disutility from the premium as expected.

3.6 Discussion of the results

This study examined how farmers value different features of Index-Based Pasture Insurance (IBPI) using two economic models: Conditional Logit (CL) and Latent Class (LC). The results offer a perspective on what farmers are willing to pay for when protecting their livelihoods from drought. One key takeaway is the importance of clear communication. Farmers in both models appreciated transparency, preferring regular updates on the insurance index's performance. This highlights the need for insurance providers to be upfront and informative. Building trust through transparency is crucial for encouraging farmers to participate in IBPI programmes. The study also sheds light on how farmers prefer to receive their insurance payouts.

Interestingly, feed emerged as the preferred reimbursement method across both models. This makes perfect sense when you consider the logistical challenges faced by farmers in remote areas. Accessing essential supplies like feed can be difficult, and IBPI, which reimburses feed, directly addresses this concern. The findings on vouchers were less clear-cut. While the first model showed no significant preference, the second indicated a positive voucher value. More research is needed to understand this inconsistency fully.

The impact of basis risk, the chance of receiving a low payout despite suffering losses, presented a more complex picture. Farmers with higher education were less fazed by basis risk, suggesting a better grasp of the concept. However, the first class identified in the LC model exhibited a positive coefficient for basis risk. This could be due to a misunderstanding that needs to be addressed. Improved communication strategies can help farmers understand basis risk and make informed decisions about IBPI. The most important finding of the LC model is the identification of two distinct farmer classes with varying preferences. This shows the importance of tailoring IBPI products to different segments of the farming population. Not all farmers are the same, and a one-size-fits-all approach won't work.

The study also found that while education played a role in how farmers perceived basis risk, other socioeconomic factors like age, wealth, or herd size didn't significantly influence which class a farmer belonged to. Livestock sales were the only factor associated with class probability, but this needs further investigation. When we delve into the preferences of each class, some interesting differences emerge. Class 1 farmers valued transparency, feed reimbursement, and even basis risk (potentially due to a misunderstanding). They also didn't show a strong preference for lower premiums.

In contrast, Class 2 farmers prioritised lower basis risk, premiums, vouchers, and feed as reimbursement methods. Transparency, however, was seen as less important in this class. The study acknowledges some limitations. There's a possibility that farmers might misunderstand basis risk, highlighting the need for improved communication methods. Additionally, the differing voucher preferences between the models and the lack of influence from most socio-economic factors require further exploration. A larger sample size could also strengthen the generalizability of the findings.

4. Conclusion and recommendations

In most cases, drought risk overstretches traditional mitigation and coping strategies capacity, causing vulnerable subsistence livestock farmers to slip into poverty and remain trapped; because of this, scholars and policymakers commend agricultural insurance, particularly index-based insurance, as a supplementary risk management mechanism owing to its unique advantages (Miranda and Farrin 2012). The South African Insurance Association (SAIA) highlighted the need to design an IBPI that is likely to be adopted by subsistence livestock farmers in South Africa (SAIA 2019). As a result, this study gives insight into the preference of subsistence livestock farmers for IBPI. Since the South African agricultural insurance sector does not offer IBPI, this study used the discrete choice experiment approach with a random sample of 110 subsistence farmers to assess farmers' preferences for hypothetical IBPI contracts within Mulima Village, Makhado District Municipality, Limpopo Province, South Africa.

The results reveal that subsistence livestock farmers prefer more transparent IBPI contracts, which means that providing farmers with regular information regarding the index's performance improves their likelihood of adopting IBPI. In addition, providing regular information about weather conditions can assist farmers in improving their farming practices in the upcoming seasons and implementing corrective measures ahead of bad weather. This communication needs to be timely and frequent. PepsiCo adopted a similar approach in India, offering capacity building and information exchange through index insurance products. Through SMS, policyholders receive technical advice on production practices, weather information, and advisories (Hazell et al. 2010). Therefore, insurance providers can expand this attribute by offering different information to assist farmers in accomplishing their farming goals while maintaining sufficiency and profitability.

Subsistence livestock farmers also prefer IBPI, which reimburses insurance claims in feed and vouchers compared to cash. Therefore, agricultural insurance providers must consider designing IBPI products that can pay insurance claims using different methods, such as cash, vouchers, and feed, to attract large economies of scale relevant to their preferences. This customisation can solve other procurement challenges concerning supplementary feed and other crucial farming services. Another critical issue is basis risk since the large body of literature reports that it reduces the likelihood of taking up IBPI. This study also shows that, on average, subsistence livestock farmers have significant negative sensitivity to basis risk.

Additionally, the results indicate that education reduces the negative impact of basis risk on demand for IBPI because farmers with a high level of education significantly opted for IBPI contracts with high basis risk. Therefore, insurance providers must provide more specific educational programmes on index insurance to improve uptake. However, the LC analysis observed significant heterogeneity regarding basis risk. About 53% of subsistence livestock farmers did not derive marginal disutility from basis risk, while 47% of farmers significantly derived marginal disutility from basis risk. Given this evidence, insurance providers must consider ways to address the adverse effects of basis risk on WTP for IBPI. This suggestion is crucial in the South African agricultural insurance sector because basis risk complicates the regulatory framework for insurers. For instance, South Africa's regulatory framework for IBPI is still in the approval stage; therefore, designing index insurance that exhibits a minimal basis risk is essential.

To address the negative effect of basis risk on the preferences for IBPI, insurance providers can collaborate with the government to subsidise a portion of the IBPI premium. Some studies reported that the negative effect of basis risk on WTP decreases when the premium is subsidised (Gaurav and Chaudhary 2020; Jensen, Mude, and Barrett 2018). Also, Mahul and Stutley (2010) conducted a survey combining 65 developing and developed countries and found that approximately two-thirds of the countries provide substantial subsidies for agricultural insurance. Such subsidies can also help in terms of premiums since this study found that farmers derive negative marginal utility from premium attributes, which means they prefer IBPI contracts with a lower premium. Another way of minimising the effect of basis risk is to cover low-frequency high covariate risks such as drought that affects many farmers simultaneously in a region. As a result, the losses of individual farmers are more likely to correlate to the index (Hazell et al. 2010).

Moreover, there is a mounting interest in using satellite measurements such as vegetative index, soil moisture, and cloud cover to design index insurance products with limited basis risk. However, the shortcoming of using the latter indexes is that farmers might exhibit protesting behaviour against the underwriting index-based contract based on "unobservable" indexes, which brings in the importance of the transparency attribute when designing index insurance. Regarding the influence of socioeconomic characteristics on farmers' preferences for IBPI, loss aversion and risk aversion do not influence the adoption of IBPI. Conversely, several studies found that risk aversion and loss aversion significantly influence uptake for index insurance (Hwang 2021; Lampe and Würtenberger 2020; Visser, Jumare, and Brick 2020). However, since the sample size of this study is relatively small compared to other similar studies, this study cannot strongly confirm the latter contrast.

Additionally, it was observed in this study that farmers with sizeable arable land are more likely to adopt IBPI. The latter correlation suggests that policymakers need to provide subsistence farmers with better access to land to promote general entrepreneurship among subsistence livestock farmers and desire to seek resilience to climate change through adopting the latest technologies, not limited to IBPI. Above all, the findings of this study suggest that IBPI contracts that do not account for the heterogeneity of preferences regarding crucial attributes might not realise significant demand. As a result, insurance providers must consider the diversification of features of IBPI after observing all regulatory requirements. The limitations of this study are the small sample size, choice experiment hypothetical biases, and the assumptions regarding diminishing sensitivity and probability weighting. As a result, this study suggests that further research be conducted using different methods, such as contingent ranking and paired comparison, using a large sample size. In addition, the approach to analysing how loss aversion affects farmers' preferences can be improved using choice experiment data pivoted around the reference alternative or the status quo (Mao et al. 2019; Masiero and Hensher 2010; Scott and Witt 2020).

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