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Weather index insurance in South Africa: An integrated approach to farmers' willingness-to-pay intentions

Mpho Steve Mathithibane and Bibi Zaheenah Chummun*

Graduate School of Business and Leadership, University of KwaZulu-Natal, Westville Campus, Durban, South Africa

*Corresponding author email: chummunb@ukzn.ac.za

Abstract

Weather index insurance is an emerging risk management tool in the African agricultural landscape specifically designed for low-income smallholder farmers that are vulnerable to weather related hazards. This insurance solution remain unexplored and commercially unavailable within the South African environment. However, there is an ever-increasing need for risk transfer mechanisms, particularly in the era of climate change and increasing drought events. The paper assesses potential demand for index-based insurance among maize farmers through a hypothetical market scenario, investigating willingness-to-pay and prevalent factors influencing the decision-making process. Quantitative research design was used. Doing so entailed employing structured surveys which were completed by 224 farmers. From this number, 86% of farmers demonstrated positive intentions towards adopting index insurance. A structural model was then constructed which identified insurance culture and risk perception as impactful behavioural constructs. Logistic regression models identified gender, education, access to credit and group membership as significant socio-economic drivers influencing willingness-to-pay intentions. The research findings advance the understanding of the smallholder producer market in South Africa which may ultimately assist in directing future product design and distribution efforts.

Keywords: Weather index insurance; Smallholder farmers; South Africa; Willingness-to-pay.

JEL Classification: G22, O13, P43

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1. Introduction and background

Crop production in South Africa mostly takes place under rain-fed conditions where aberrations in rainfall have the potential to adversely affect crop yield (GCIS, 2017). South Africa is classified as semi-arid country with a highly developed and industrialised agricultural sector which contributes substantially to food security systems in Africa. The country, an upper middle-income economy with diversified economic activities produces 17% of Africa's maize crop (Davis-Reddy & Vincent, 2017), where maize is a major staple food, for both human and animal consumption. In addition, maize plays a key role as a base material in the manufacturing sector. The agricultural sector in South Africa is commonly referred to as a dual economy, where well-capitalised and mostly White commercial farmers operate in parallel with the majority resource-constrained Black African smallholder farmers. It is estimated that smallholders, excluding a projected 1.5 million subsistence farmers, outnumber commercial farmers ten-fold, with a projected 400 000 smallholder farmers and 40 000 commercial farmers (National Treasury, 2015). Paradoxically, commercial farming accounts for most of the country's crop production, with the remaining portion accounted for in smallholder and subsistence farming (GCIS, 2019). This uneven participation, and resultant skewed distribution of resources, including land, machinery and irrigation systems contributes to South Africa being one of the most unequal societies in the world with a Gini coefficient of 0.63 (World Bank, 2018).

Increasing threats of poverty, inequality and unemployment have lead the national government to develop a New Growth Path through its strategic plan of action – The National Development Plan 2030. In this strategic roadmap, transformation and development of the agricultural sector is given prominence; smallholder farming is earmarked to create over 1 million jobs with the backing of government financial and technical support (National Planning Commission, 2012). The plan is further aligned with the African Union Agenda 2063 which espouses a prosperous Africa based on inclusive growth and sustainable development. Among others, where modern and productive agriculture contributes to household and national food security across the continent (Africa Union Commission, 2015).

The new era of smallholder development in South Africa faces an inherent threat: the challenge remains the provision of adequate insurance solutions for smallholder farmers in light of weather-related production risk, intensified in the form of current and future climate change (Partridge & Wagner, 2016).

According to Kotir (2011), food security in Sub-Saharan Africa, classified by food availability, food accessibility, food utilisation and food stability, is highly vulnerable to the impacts of climate change due to environmental effects such as prolonged dry spells and shorter growing days but also equally as prevalent are non-environmental factors which include the inability of farmers to adapt due to lack of tools, techniques and resources in the form of technology and irrigation. It is said that the 21st century is likely to see Africa experience record high temperatures in addition to erratic rainfall and persistent drought (IPCC, 2014).

Although traditional indemnity-based crop insurance exists in South Africa, precisely to mitigate against production risk due to weather variables, the products are prohibitively expensive (GreenCape, 2018) and not suitable for the risk transfer needs of smallholder farmers (Carter *et al*., 2018), as evidenced by an insurance penetration rate of less than 1% (de Klerk, Fraser & Fullerton, 2013). In response to market failures that are evident in South Africa, and the rest of Africa, Carter *et al*. (2014) identify index-based insurance as the ideal solution for the uninsured as it has the potential to create access to formal insurance for millions of smallholders. It is long assessed that uninsured risk results in under-developed insurance markets, the effects of which are vicious cycles of under-investment, low agricultural yields and the persistence of poverty (Castillo *et al*., 2016). It remains untested if smallholder farmers in South Africa are open to participating in index insurance markets given that they have developed alternative, long-standing, traditional risk mitigating strategies such as crop diversification, and even resorting to reducing crop production in times of uncertainly. Among other methods, these intentions can be tested by a stated preference survey expressed in the form of willingness-to-pay. Willingness-to-pay is defined as the maximum amount of money a person is willing to pay unusually for a non-market product or service. According to Carter *et al*. (2014), willingness-to-pay levels can be considered as the minimum latent demand for weather index insurance. This approach is a direct and inexpensive way of interacting with potential market participants.

The focus of this paper is on smallholder farmers. This emphasis is important because, apart from South Africa, smallholding is the dominant farming form in Africa (Obeng-Odoom, 2013). Such a scope, therefore, provides a wider application for the paper generally. Specifically, the objective of this study is to investigate smallholder farmers’ willingness-to-pay intentions; and further identify the socio-psychological and socio-economic determinants that would influence willingness-to-pay decisions for weather index insurance in South Africa. According to Njue *et al.* (2018), where index insurance products are lacking, or uptake is low, studies find that a knowledge gap exists about understanding factors influencing farmers' participation and uptake of index insurance contracts. Moreover, King and Singh (2018) assess that where relevant studies are conducted, research predominantly focuses on economic drivers, with little emphasis on the psychological factors. In most cases, findings on economic drivers behind index insurance purchase decisions are highly inconsistent and incomparable, indicative of environmental and cultural dynamics influencing farmers' perceptions of risk and subsequent participation or lack thereof in insurance schemes (Addey *et al.*, 2020). The motive of the present study is to fill the empirical knowledge gap in this emerging dimension of risk mitigating research. In the context of this study, smallholder farmers are defined as those that produce at a primary level for household consumption and markets; therefore, farming is consciously undertaken in order to meet the needs of the household and derive a source of income. These producers generate annual turnover of between R50 000 – R5 million which is equivalent to a range of USD 3400 – USD 340 000 (DAFF, 2018). Based on empirical data, integrated models and theories, this paper finds that smallholder farmers have great interest in weather index insurance as a risk reduction solution, rebuffing traditional thinking that there is no room for insurance in this sector due to poor understanding of risk factor. The rest of the paper presents this argument in six sections, respectively examining the state of the literature, the conceptual framework underpinning the study, the methodology, empirical data and analysis thereof as well as policy implications and recommendations.

2. Literature review

2.1. Weather index insurance

Weather index insurance products are most effective in providing cover for progressive perils such as drought and excessive dry spells where crop deterioration is not marked by a single event but rather occurs over a period of time (Shirsath *et al*., 2019). South Africa is particularly prone to drought events which negatively affects agricultural production where subsequent impact extends to employment and food security. Walz *et al.* (2018) asses that extreme drought events occur in South Africa every two to seven years. In 2015/16, large parts of the country were declared disaster areas due to drought, a projected 250 000 farmers were affected, the majority being vulnerable smallholders who generally lack effective coping mechanisms, moreover, 6 million lives were indirectly affected (Ncube & Shikwambana, 2016). Over the long-term, drought accounts for over 40% of all agricultural losses in South Africa (Sasria, 2018). The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report finds that Africa stands to benefit from integrated climate adaptation, mitigation and development approaches. One of the strategies is the use of weather index insurance solutions to strengthen adaptive capacity (IPCC, 2014:33).

Weather index insurance is a risk transfer contract between the insurer and insured where in exchange for a premium the insurer accepts risk and assumes liability for future claim obligations that are triggered on the occurrence of a predetermined weather parameter measured on the basis of rainfall, temperature, or moisture satellite-driven data. Index insurance is built on the concept of weather derivatives which have been reconfigured for the agricultural sector. A key feature of this contract is that crop yields are modelled and losses are indirectly assessed using proxies or an index as an estimate of the level of damage rather than direct on-field assessments (Ward, 2017). This approach results in significant savings on loss verification, reduced administration, and elimination of fraud, moral hazard and adverse selection associated with traditional forms of insurance (Matsuda & Kurosaki, 2019; Weber, 2019). As such weather parameters of the insurance contract should correlate as closely as possible, the insured weather hazard and subsequent reduction of crop yield (Ahmed *et al.*, 2017). Failure to correlate losses to crop yield results in basis risk, which many scholars and practitioners (Stoppa & Dick, 2018; Ward *et al.*, 2019) agree is the main drawback of index insurance.

Basis risk results in contract failure, that is, premiums are paid, losses incurred, but no indemnity payments are made, or losses are not incurred at farm level yet the index is triggered, and payments are made due to imperfect correlation (Carlos, 2016). If pay-outs are nil or too low compared to the value of loss intended to be paid by the policy, index insurance fails to meet its primary ‘protection’ objective. On the other hand, pay-outs that are too high compared to actual losses undermine the plausibility of insurance schemes (WFP, 2017). Therefore, farmers are generally sensitive to basis risk, impacting their willingness-to-pay, for every 1% increase in basis risk, farmers would need to be compensated with a 3% – 4% reduction in insurance premium (Ward & Makhija, 2018). Basis risk is endemic to index insurance contract design even if better agronomic models can be developed, natural limits exist because one is applying mathematics to a series of natural processes, which can be extremely complex (Carlos, 2016). In essence, basis risk represents a trade-off for lower premiums, reduced administration and many positive developmental impacts of weather index insurance.

2.2. Developmental impact

Where index-based insurance is offered, significant development impacts are observed with respect to reduced vulnerability, improved resilience, improved welfare and greater economic participation. Index-based products often benefit broader financial inclusion objectives. For example, improved access to credit for farmers with little to no collateral, where insurance is a substitute for traditional security (Johnson, 2013). South Africa has a well-established and sophisticated banking system similar to many developed nations, along with a high number of banked clients. However, smallholder farmers have experienced slow growth in credit supply and receive the lowest level of credit in comparison to other sectors of the economy (Chisasa & Makina, 2012). A financial inclusion index, which relied less on traditional measure of owning a bank account, but features various inputs on financial asset ownership such as credit, mortgage, investments and savings, reveals that households in rural areas of the country, in particular Black Africans, are the most excluded, this is intrinsically associated with high levels of poverty (Matsebula & Yu, 2020). Around 12% of smallholders in South Africa have access to credit (World Bank, 2016), which is a fundamental driver of working capital for farm productivity.

In their investigation on drivers of financial inclusion, Tita and Aziakpono (2017) argue that formal access to credit and the provision of appropriate insurance solutions has the ability to reduce income inequality in the short and long term. It is no surprise that practical evidence from an index insurance scheme in Kenya reported that 97% of all insured farmers were able to access credit (World Bank, 2017), therefore, demonstrating the complementary relationship between credit and insurance linkages.

Studies further show that weather index insurance adoption leads to significant increases of fertilizer and higher quality seeds among small-scale farmers resulting in improved crop yield (Sibiko & Qaim, 2017). Chemical fertilizer is expensive, and there is potential for significant crop losses under adverse conditions, for this reason, farmers are often reluctant to apply chemical fertilizers in an environment of unmanaged risk (Hill *et al*., 2019). Lastly, farmers who use index insurance have the propensity to adopt new technologies (Karlan *et al.*, 2014). This is because insurance uptake most often changes farmers' interpretation of the operating environment and ultimately reduces risk aversion, which is a major driver of agricultural technology adoption (Haile *et al*., 2019). For these developmental imperatives and broader political considerations, most national governments in developed countries support index insurance schemes through subsidies and establishing an appropriate regulatory framework (Ward *et al*., 2019).

2.3. Demand limitations

Despite the developmental benefits, index insurance uptake in Africa continues to be low estimated at less than 10% penetration in some regions (Bellisa *et al*., 2020). Anecdotal evidence suggests that low uptake is attributable to poor insurance culture (Jensen & Barrett, 2016), low levels of insurance awareness (Aditya *et al*., 2018), inexperience with financial products and lack of premium subsidies (Farrin *et al*., 2016). Intuitively, financial constraints are a prominent reason for low uptake of insurance by low-income smallholder farmers. However, many scholars hold an opposing view and contend that the major reason for low uptake is generally a poor understanding of farmers' willingness-to-pay and the factors that influence their decision to pay for index solutions (Fonta *et al*., 2018), while neoclassical economic models of utility maximisation and marginalism have failed to explain low demand (Würtenberger, 2019).

As part of the effort to support the application and implementation of index insurance in South Africa, the South African Insurance Association (SAIA), representing the interest of insurance providers, has submitted an application to the regulatory authorities for industry-wide approval to open the market for index insurance as a class of business (SAIA, 2019). This paper is, therefore, further intended to provide empirical evidence in the current discourse as well as to uncover new insights and contribute to the current literature by describing the extent to which socio-psychological, socio-demographic, and socio-economic variables influence willingness-to-pay intentions for index insurance. Socio-psychological variables explored in this paper are grounded on the Theory of Planned Behaviour (TPB) which is a behavioural predictive model. In TPB, intentions to perform a behaviour are conceptualised as the closest precursor to the actual behaviour (Judge, Warren-Myers & Paladino, 2019). A logistic regression model is performed to evaluate socio-demographic and socio-economic drivers that influence the decision and willingness-to-pay for index insurance. Together, the TPB and logistic regression model form an integrated approach and framework to addressing willingness to pay intentions of smallholder farmers.

3. Conceptual framework

TPB (Ajzen, 1991) is a socio-psychological model for understanding and predicting human behaviour. In TPB, there are three independent determinants of an individual's intentions which account for considerable variance in actual behaviour: attitude, subjective norm, and perceived behavioural control (Ajzen, 2015). Attitude assesses the favourable or unfavourable view towards the behaviour, subjective norms reflect social pressure or motivation to perform the behaviour and perceived behavioural control is indicative of the person's resources and opportunities to perform the behaviour (Ajzen, 1991). The TPB is widely used in various disciplines to better understand human behaviour, areas of application include: healthcare (Al Hasan *et al*., 2019), information systems (Jokonya, 2017), agriculture (Akyüz & Theuvsen, 2020), including agricultural insurance (Abd Aziz *et al*., 2015). TPB is well-researched through meta-analysis for its efficacy as a predictor of intentions and subsequent behaviour (Jalili & Ghaleh, 2019).

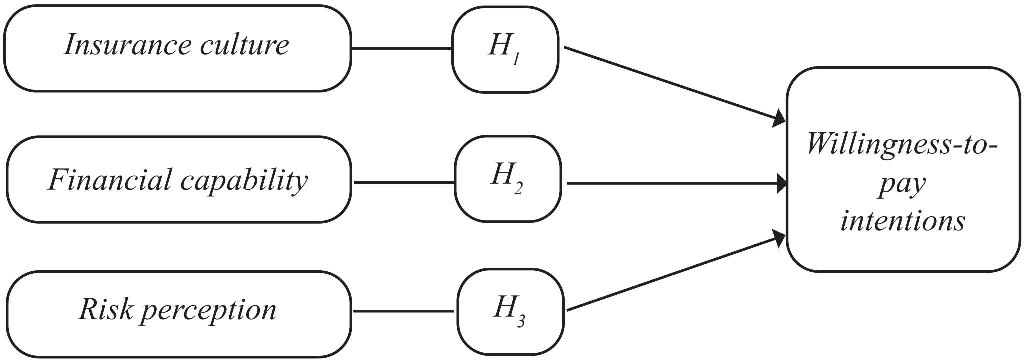
In this research, these conceptual constructs are used to predict willingness-to-pay intentions are have been adapted to insurance terminology where attitude – the positive or negative views towards agricultural risk management are reflective of risk perception; subjective norms – culture towards insurance usage reflective of insurance culture; and perceived behavioural control – the understanding of financial products and the availability of financial resources to use these products indicative of financial capability. Figure 1 depicts the conceptual framework underpinning socio-psychological variables in the form of a structural diagram, where the study lends itself to the following hypotheses:

H_1- Insurance culture has a positive significant relationship with willingness-to-pay.

H_2- Financial capability has a positive significant relationship with willingness-to-pay.

H_3- Risk perception has a positive significant relationship with willingness-to-pay.

FIGURE 1: CONCEPTUAL FRAMEWORK



Source: Derived from hypothesised relationships in this study.

The conceptual model in Figure 1 represents the socio-psychological constructs, while the empirical model in the following section features demographic and economic considerations that influence willingness-to-pay.

3.1. Empirical model

The present study investigates which significant demographic and economic factors as identified from a wide range of other similar enquiries in Africa (such as Ellis, 2017; Fonta *et al*., 2018; Sibiko *et al*., 2018) would influence willingness-to-pay for weather index insurance in South Africa. Key factors identified and tested in this study are: age, gender, marital status, education, experience and household size from a demographic perspective; and access to credit, turnover, farm size, group membership and risk coping strategy from a socio-economic point of view. These factors and their influence on willingness-to-pay were empirically tested using logistic regression.

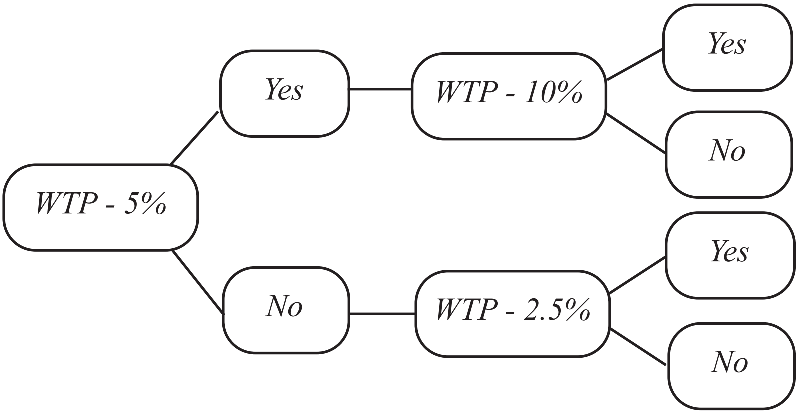
$$\pi_i = Pr(Y_i = 1|X_i = x_i) = \frac{\exp(\beta_0 + \beta_1 x_i)}{1 + \exp(\beta_0 + \beta_1 x_i)} \tag{1}$$

Where Y is the binary response variable, the variable Y_i represents the willingness-to-pay, with a value of 1 if the respondent indicates yes or 0 if the respondent replies no. X represents (X_1, X_2, ...,) a set of explanatory or independent variables which can be categorical, continuous, or a combination. Lastly, x_i is the observed value of the explanatory variables for observation i.

3.2. Contingent valuation

Contingent valuation is highly recommended for willingness-to-pay studies and used in instances where there is no or little market information. It has been used in previous studies to solicit willingness-to-pay for weather index insurance (Aditya *et al*., 2018; Ellis, 2017; Fonta *et al*., 2018). The double-dichotomous choice with close ended questions contingent valuation approach is preferred in this study because of its efficiency and popularity among other variations (Park & MacLachlan, 2008). The method entails a willingness-to-pay question asked at an initial starting price with respondents replying by indicating 'Yes' or 'No'. Based on the response, a follow-up question is asked with a new upper and lower threshold. The upper threshold is asked to respondents that answered 'Yes', the lower bound is asked to respondents that answer 'No' to willingness-to-pay (Cameron & Quiggin, 1994). The starting price for this study was set at 5% of crop harvest which is the minimum price for a commercial weather index insurance programme in Ghana (Adjabui *et al*., 2019), and closely aligned with the current commercial rate of 4% for traditional crop insurance in South Africa (World Bank, 2016). The choice variables are illustrated in Figure 2.

Figure 2: Willingness-to-pay scenarios



Source: Derived from the contingent valuation approach in this study.

The scenario and willingness to pay questions were presented to participants as follows:

Weather index insurance is an alternative form of crop insurance that uses a measure of rainfall to cover crop damage for farmers within a defined geographical area. For example, if rainfall is below a pre-determined level over the crop planting season, then insurance pay-outs will be made to all insured farmers in that area without on-field farm verifications. If rainfall is above a defined level for the area, then there will be no pay-out. The insurance is intended to cover against adverse variations in regional rainfall. It should be noted that not all farms in the defined area will receive an equal amount of rainfall, therefore, there is a possibility that farm level crops can be damaged as a result of a lack of rainfall, but no insurance pay-out will be made if the overall rainfall index in the area has not fallen below the pre-set level.

Based the scenario, would you be willing to pay 5% of the value of your crop harvest for weather index insurance? If the answer is 'Yes' to the first question, would you be willing to pay 10%? If the answer is 'No' to the first question, would you be willing to pay 2.5%?

4. Data

4.1. Population and sample

The study was conducted following a quantitative research approach in the central to eastern regions of South Africa, in Free State, North West, and Mpumalanga province where most of the maize cropping activities take place (DAFF, 2019). The population under investigation was a list of 1 774 rural-based smallholder farmers, obtained from the Land and Agricultural Development Bank of South Africa (Land Bank) featuring recipients of loans and/or grant funding issued between 2015 – 2019. Land Bank is a state-owned development finance institution with a core mandate for the promotion, facilitation and support of agriculture by providing adequate financial services. From the population, over 90% of beneficiaries were Black African farmers. As highlighted by Sebola (2018), most smallholder farmers in South Africa are Black Africans in rural areas operating under conditions where vast inequality gaps persist driven by the racially skewed history of colonialism, apartheid and land dispossession in the country. The democratically elected government has since 1994 introduced various land reform programmes to close the gap, but the economic and wealth inequalities remain prevalent. As of 2019, 10% of the population, mostly White South Africans, controlled an estimated 95% of the country's wealth; where wealth is measured in terms of the financial value of assets owned (Stats SA, 2019). This form of stratification makes South Africa one of the most unequal countries in the world (Obeng-Odoom, 2020). In such stratified societies, there is likely to be unrest, social and political instability caused by persistent inequality and poverty.

The Taro Yamane sample size calculator for stratified random sampling technique is highly relevant. The advantages of stratified random sampling are that it is proportionally representative of the population; there is minimum sample bias, and the exact representativeness of the sample is known (Dubey *et al*., 2017). Based on the sample size calculator, a sample of 326 was derived using a 95% confidence level. From the surveys conducted, a total of 224 responses were received from study participants, resulting in a 68.7% response rate.

4.2. Measurement instrument

A structured questionnaire in the form of a survey was used to collect primary data. The measurement items for insurance culture, financial capability, and risk perception developed on a five-point Likert scale modified from various studies, including applying recommendations on constructing a TBP questionnaire (Ajzen, 2006) and guidance from other studies applying TBP for insurance purchase decisions (Brahmana *et al*., 2018; Weedige *et al*., 2019). The adopted measurement scales are featured in Table 1. The questionnaire additionally featured demographic, socio-economic, farm-specific closed-ended questions to get a better understanding of the profile of farmers and to also form the basis of explanatory variables for willingness-to-pay intentions.

Table 1: Measurement Scales

Constructs
Insurance Culture
I have a good understanding of how crop insurance works.
I have considered using crop insurance to protect my assets.
I understand that paying crop insurance premiums does not guarantee that there will be a claim pay-out.
Financial capability
I have access to emergency savings for farm operations.
I have sufficient funds to carry on my farming operations for the next year
I manage farm operations according to a planned budget.
Risk perception
I plan carefully for the next crop production cycle in order to avoid losses.
I make planting decisions based on weather reports.
I am more cautious because of previous loss experience.
Compared to other farmers, I would say I take more risks in the crop production cycle.

Source: Authors' illustration

4.3. Data analysis

Structural Equation Modelling (SEM) using the maximum likelihood method was used to investigate the proposed relationships of latent constructs that influence willingness-to-pay for weather index insurance. SEM is a multivariate technique that is well suited for testing various hypothesised relationships between variables (In'nami & Koizumi, 2013). SEM comprises two subsets of models: a measurement model and a structured model. The first step in SEM is to specify the measurement model and conduct Confirmatory Factor Analysis (CFA) to test for unidimensionality, validity and reliability of items measuring the latent constructs (Awang *et al*., 2017). Unidimensionality was tested by considering the acceptability of the factor loadings of all measuring items. Reliability of the measurement items was tested using the Cronbach's alpha and composite reliability. The validity of the measurement model was examined by determining convergent and discriminant validity. A logistic regression model was used to identify demographic and economic factors that are associated with willingness-to-pay. Logistic regression is a type of multivariable analyses used with increasing frequency because of its ability to model linear and non-linear relationships between a dichotomous dependent variable (willingness-to-pay) and one or more independent variables (Park, 2013).

5. Results

A total of 224 responses were obtained. This level of response was considered sufficient for SEM analysis, which exceeds the 200 threshold considered a minimum for such analyses (Westland, 2015). A profile of the respondents as summarized in Table 2 indicates the following: Majority of the respondents were male (81%), between the ages of 45 and 54 years (28%), married (66%), having obtained secondary school education (52%) and have at least one insurance policy (70%).

TABLE 2: SUMMARY PROFILE OF RESPONDENTS

Description		Frequency	Percentage
Gender	Male	181	81%
	Female	43	19%
Age	18 – 34	37	17%
	35 - 44	46	20%
	45 - 54	62	28%
	55 – 64	39	17%
	65 and older	40	18%
Race	Black African	211	94%
	Coloured	2	1%
	White	11	5%
Marital status	Married	147	66%
	Single	57	25%
	Widowed	14	6%
	Divorced	4	2%
	Prefer not to sat	2	1%
Household size	1 – 5	158	71%
	6 – 10	66	29%
Education	No formal education	15	7%
	Primary education	29	13%
No formal education	Secondary education	118	52%
	Tertiary education	62	28%
General Insurance	Yes	157	70%
	No	67	30%

Source: Authors' computation.

Based on the results of the double-dichotomous contingent valuation approach where 5% premium rate is the starting bid, willingness-to-pay statistics are outlined in Table 3:

Table 3: Willingness-to-pay Statistics

Willingness-to-pay (WTP)	**5%**		**10%**		**2.5%**		**Aggregate WTP**	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Yes	175	78%	77	44%	17	35%	192	86%
No	49	22%	98	56%	32	65%	32	14%
Total	224	100%	175	100%	49	100%	224	100%

Source: Authors' computation.

An aggregate 86% majority of farmers are willing to pay for insurance to mitigate and reduce effects of weather-related risk on their livelihood. When asked about the premium rate farmers are willing to pay as a percentage of their crop harvest (turnover): 78% of farmers reported 5%, from this number a further 44% indicated that they would be willing to pay as much as 10%. Of the farmers that were not willing to pay the initial 5% bid price, a moderate 35% indicated that a 2.5% premium would be more affordable. For those that are not willing to pay any amount, the most prevalent reason was that there are other key priorities (91%) competing with insurance purchase.

5.1. Confirmatory factor analysis

CFA was conducted and the measurement model was examined for any potential problematic estimates, specifically those with low factor loadings. All factor loadings for latent constructs retained in this study were positive and above the recommended threshold of 0.50 for items that are newly developed (Awang, 2015). Therefore, the items loaded in a satisfactory manner and unidimensionality was achieved. The goodness-of fit indices to assess the measurement model adequacy, which addresses construct validity verified validity of latent constructs (CMIN=2.27, CFI=0.97, TLI=0.95, GFI=0.95 and RMSEA=0.08) based on the criteria as set in (Hox & Bechger, 1998).

Table 4: Reliability and Validity Assessment

Construct	Cronbach alpha	Composite reliability	AVE	Discriminant Validity
Insurance culture	0.81	0.83	0.78	0.88
Financial capability	0.84	0.86	0.81	0.90
Risk perception	0.74	0.84	0.75	0.87

Source: Authors' computation.

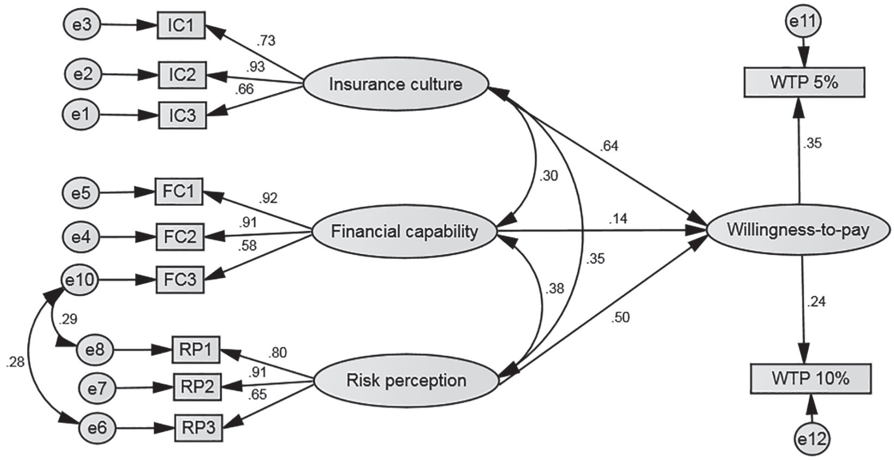
As calculated in Table 4 Cronbach alpha and composite reliability excess 0.7 for all the constructs indicating high internal reliability and consistency. Cronbach alpha of 0.7 and above is considered acceptable (Hinton & Platt, 2019) as a measure of internal consistency, whereas composite reliability above 0.6 indicates reliability and internal consistency of latent variables (Awang, 2012). Convergent validity to ascertain the degree to which each measurement item correlates with the socio-psychological variables is determined from the average variance explained (AVE) values. The reported AVE ranges from 0.75 to 0.81, which is greater than the threshold of 0.5 (Hair *et al*., 2014). Discriminant validity is determined by calculating the square root of AVE, which should exceed the correlation of latent constructs in the measurement model. The factor correlation matrix indicated that the largest squared correlation between any pair of constructs is 0.38 between financial capability and risk perception, while the smallest AVE is 0.87. The respective measures are acceptable for this study since the aforementioned results confirmed unidimensionality, reliability, and validity of the latent constructs.

5.2. Structural model

The hypothesised structural model in Figure 3 with the visual display of estimates shows the initial measurement model of this study, with linkages between constructs in the model, the research framework and the stated hypotheses to be tested. To accept or reject a hypothesised relationship, the significance testing decision rule was applied at a significance level of $p<0.05$.

The goodness-of fit indices to assess the structural model reported satisfactory model fit following modification of the model and removing willingness-to-pay variable of 2.5% which had a negative factor loading on the willingness-to-pay variable (CMIN=2.41, CFI=0.95, TLI=0.93, GFI=0.93 and RMSEA=0.08). The SEM model features 66 distinct sample moments and 29 distinct parameters to be estimated, which leaves 37 degrees of freedom (df) based on the identified model, and a chi-square value of 89.423 with a probability level equal to p=0.000.

Figure 3: Reliability and Validity Assessment



Source: Authors' computation.

Insurance culture (path estimate=0.64, p=0.001), and risk perception (path estimate=0.50, p=0.01), determinants both have a statistically significant ($p<0.01$) positive influence on willingness-to-pay. While financial capability (path estimate=0.14, p=0.44), is identified in the structural model, but this is neither substantial nor statistically significant. The positive sign though implies that farmers who have the financial capability are likely to a lesser extent as compared to other constructs tested in the study, to consider weather index insurance as a solution. The findings on financial capability are in contrast to those by Abd Aziz *et al*. (2015), deploying multiple regression analysis, the authors suggest that perceived behavioural control, which reflects the ability and opportunity both financially and otherwise, has the highest impact as a predictor on the intention to participate in agricultural insurance in Malaysia, with a standardized beta coefficient of 0.44. Based on the results of the hypotheses testing, H_1 and H_3 are supported and have a large positive effect of willingness-to-pay; H_2 is not supported by the study results on the grounds of a small non-significant effect on willingness-to-pay.

5.3. Logistic model

According to Ranganathan *et al.* (2017), the key to a meaningful logistic regression model is the choice of appropriate predictor variables to include in the model. The inclusion of as many as variables possible can dilute true associations, lead to large standard errors with wide and inaccurate confidence intervals. Therefore, a Pearson Chi-square was performed on all categorical variables to identify factors with significant associations with the dependent variable for inclusion in the logistic regression. The authors advise that a more liberal statistical test of significance ($p<0.2$) should be applied for setting the inclusion criteria since the purpose is to identify potential predictor variables rather than hypothesis testing. Following the test gender, qualification, turnover, access to credit and group membership were retained in the model. The results are presented in Table 5.

Table 5: Variables in Logistic Regression

Variables	Beta	S.E	Wald Test	P (Significant)	Exp(B)
Gender	0.814	0.415	3.848	0.050	2.256
Qualification			8.728	0.033	
Primary education	-1.720	0.749	5.276	0.022	0.179
Secondary education	-1.875	0.641	8.550	0.003	0.153
Tertiary education	-1.531	0.685	5.001	0.025	0.216
Turnover			7.354	0.118	
R250 001 – R500 000	-1.083	0.549	3.886	0.049	0.339
R500 001 – R1 000 000	-0.73	0.626	0.77	0.782	0.841
R1 000 001 – R2 000 000	0.311	0.902	0.119	0.730	1.365
More than R2 000 001	1.077	0.729	2.183	0.140	2.935
Access to credit	0.833	0.454	3.373	0.066	2.301
Group membership	0.677	0.375	3.258	0.071	1.967
Constant	-2.920	1.271	5.281	0.22	0.540

Source: Authors' computation.

The logistic regression was statistically significant, chi-square = 33.876, df = 10, p=0.000 and the model satisfactorily fits the data as evidence in Hosmer and Lemeshow test results (chi-square = 7.325, 8 degrees of freedom, p=0.289). A non-significant Hosmer and Lemeshow chi-square in this regard indicates that the data fit the model well (Wuensch, 2020). The model explained 21.6% (Nagelkerke R^2) of the variance in willingness-to-pay and correctly classified 79.5% of the variance. These values are acceptable and within the region of other willingness-to-pay studies applying the contingent valuation method (Abdullah *et al.*, 2014).

From the results reported in Table 5 Gender (p=0.05) and education (p=0.03) were statistically significant factors influencing willingness-to-pay at a 5% confidence level. Access to credit (p=0.066) and group membership (p=0.071) were statistically significant at a 10% confidence level. Males were twice (2.256) as likely to purchase weather index insurance compared to females, similarly, access to credit (2.301) and group membership (1.967) increases the chances of willingness-to-pay twice as much. While education decreases the likelihood of willingness-to-pay for weather index insurance. Although the variable turnover was hypothesised in the model to have an influence, there was no significant effect on willingness-to-pay. Similar to results in Ellis (2017), where income has an insignificant relationship with farmers' willingness to purchase insurance.

6. Discussion of results

6.1. Willingness-to-pay

Risk management is at the heart of sustainable, long-term agriculture. In addition, to weather fluctuations, more structural characteristics may substantially affect a farmer's exposure to risks (Ceballos & Robles, 2020). Within these existing dynamics, the study reports that a large number of farmers would welcome a novel risk transfer solution to alleviate some of their challenges and concerns. This is underscored by 86% of surveyed farmers reporting a willingness-to-pay for crop index insurance. The research reported here strongly complements other willingness-to-pay studies such as Fonta *et al*. (2018) reporting willingness-to-pay of 88% in Burkina Faso; Musya and Muttai, (2020) reporting willingness-to-pay of 84% for maize farmers in Kenya; Nyaaba, Nkrumah-Ennin and Anang (2019) reporting willingness-to-pay of 91% in Ghana.

6.2. Socio-psychological constructs

According to Carter *et al.* (2014), uptake of index insurance depends on farmer behaviour and the use of socio-psychological models becomes important to explaining the variance between low demand for actual market products and theoretical demand in the form of willingness-to-pay. Based on SEM results, insurance culture has a direct impact on purchase intentions. This is consistent with the literature that culture has an influence on participation in insurance markets (Zhong *et al.*, 2015). Risk perception has a significant and direct influence on willingness-to-pay. These results are similar to those reported by

Lyu and Barré, (2017) as well Adjabui *et al*. (2019), and support the assertion that smallholder farmers are risk averse and under the expected utility framework, risk averse farmers are willing to pay for index insurance (Hill *et al*., 2019).

6.3. Socio-demographics factors

Gender is a positive and statistically significant factor influencing willingness-to-pay. In particular, male farmers are shown to have an increased propensity for weather index insurance. This finding is consistent with literature from other settings highlighting that participation of female farmers in weather index insurance is lower (Nyaaba *et al.*, 2019). Gender disparity and inequality in farming remains a prevalent unresolved social issue. Female farmers earn much less income than their male counterparts (Flatø *et al*., 2017), therefore liquidity constraints might be a substantial reason for decision to participate in insurance.

Education is a negative and statistically significant factor influencing willingness-to-pay. This supports findings of Fonta *et al.* (2018) as well as Gaurav and Chaudhary (2020), however, in contrast to Ellis (2017) where better educated farmers are more likely to receive and understand the index insurance with its complexities and are more willing to purchase the product. The negative influence reported in this study is surprising considering that 70% of farmers reported having at least one personal or commercial lines insurance policy. A possible explanation is that educated farmers have a better grasp on the concept and limitations of weather index insurance as it pertains to the basis risk component. Supporting studies find basis risk to negatively impact insurance demand (Lampe & Würtenberger, 2019). In addition, better educated farmers in South Africa are likely to adopt new practice such as cover cropping, minimum-tillage, tied ridging to improve production and mitigate climate change (Myeni *et al.*, 2019), these alternative Sustainable Agricultural Practices (SAP) may reduce insurance demand. Interestingly, at levels of no formal education, demand is also low, this might be driven by limited understanding and appetite for insurance.

6.4. Socio-economics factors

Access to credit is a positive significant determinant of willingness-to-pay. Complimenting findings from Atsiaya *et al*. (2018) where access to credit is a positive coefficient which is statistically significant. By its nature, credit relaxes farmers' liquidity constraints, hence can significantly increase the probability that farming households purchase weather index insurance contracts (Haile *et al*., 2019).

Group membership is a positive significant factor influencing willingness-to-pay. The findings are consistent with research conducted by other authors (Addey *et al*., 2020; Adjabui *et al*., 2019). Group membership is critical for knowledge sharing, information dissemination, leaning platforms for innovation and building social capital, which can improve awareness and knowledge on index-based insurance. The positive impact of knowledge on uptake of weather index insurance has been well documented, and repeatedly found to increase demand (Würtenberger, 2019).

6. Conclusion and recommendations

Weather index insurance has been championed as a solution for the uninsured and a response to systemic drought risk effects of climate change that affect smallholder farmers disproportionately because of their low financial resilience and vulnerability to weather shocks. The financial constraints around this market, and perpetual challenges of access to markets, financing, and modern technology bring into question the demand for insurance. Especially in the context that insurance is viewed as a grudge purchase, represented by an immediate cash outflow without guarantee of a claim pay-out. This study takes a step in uncovering demand for index insurance and related driving factors, providing evidence that smallholder farmers are willing to adopt weather index insurance in their risk mitigating efforts.

Farmers are willing to pay for insurance, with a majority indicating that at least 5% of their turnover can be ring-fenced for insurance premium. Given that most of the participants in this study are Black, the view that Black people's 'culture' inhibit their participation in the market is questionable both as explanation for the marginalisation of the Black people and as a basis for policy. Institutional reforms to address racism, discrimination, and uneven ownership of land are more credible alternative points of emphases (see also Obeng-Odoom, 2020). This way of reframing the debate on social transformation and socio-ecological empowerment provides practical application for insurance providers with respect to pricing, while the difference between willingness-to-pay and the ultimate costs of insurance provides evidence to government on the starting point of potential subsidies to ensure that farmers are adequately covered on an ex-ante basis. This is because ex-post government disaster relief funding has proven to be unsustainable, bureaucracy-laden and untimely ineffective for many farmers (Baudoin *et al*., 2017).

Two additional important policy recommendations can be proposed. First, access to credit has long been heralded as a gateway to exponentially increase agricultural insurance uptake. This is because farmers generally seek an additional layer of security provided by insurance to enable them to repayment agricultural loans in the event of weather-related hazards. Index insurance is commonly viewed as a form of substitute security which can be leveraged by financial institutions to improve access to credit (Reyes *et al.*, 2015), especially where traditional forms of collateral such as property, machinery and vehicles are lacking, as is the case with many smallholder producers. An approach followed in many established index insurance markets is to leverage this link and bundle the provision of credit with insurance. This is the recommended distribution approach in the South African market. Fit for purpose credit-insurance bundling has an added advantage of making insurance premium more affordable because collections can be made in manageable instalments along with loan repayments, thus eliminating one of the shortcomings of standalone index insurance.

Second, it is recommended that agricultural crop insurance with its subsets finds resonance in the national policy agenda and integration in the agricultural policy framework among the many government programmes such as the flagship Comprehensive Agricultural Support Programme (CASP). By integrating insurance in government programmes, a sustainable, holistic risk management systems in build, where a system approach of comprehensive financial services and non-financial support in the form of extension services runs parallel to address farmers' challenges. Further research is required on index insurance in the South Africa context as an alternative financial inclusion solution, particularly the perceptions of insurance providers on its viability, studies on the challenges and opportunities of index insurance, as well as future studies on demand drivers for insurance and the role of education and training in enhancing insurance uptake.

Conflict of interest

The authors declare no conflict of interest.

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Biographical notes

Mpho Steve Mathithibane is a DBA candidate at the Graduate School of Business and Leadership, University of KwaZulu-Natal. He is a senior agricultural underwriter at the Landbank Insurance Company, a wholly owned subsidiary of the Land and Agricultural Bank of South Africa, where he specialises in crop insurance and reinsurance solutions for commercial and smallholder farmers. Email Address: mmathithibane@landbank.co.za.

Dr Bibi Zaheenah Chummun is a senior lecturer at the Graduate School of Business and Leadership, University of KwaZulu-Natal. She holds a PhD in Business Administration. Her research interests are in Microinsurance/Microfinance, Weather Index Insurance, Financial Inclusion, Marketing Management and Business Success. She also supervises postgraduate students in those fields and teaches Marketing Management on the Master's Programme at UKZN. Dr Bibi Z. Chummun has over 15 years of experience in academia and has held senior positions in the business industry both in Mauritius and in UK. She is originally from Mauritius, an island in Africa. Email Address: chummunb@ukzn.ac.za.

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