A Double-hurdle Model Estimation of Smallholder Commercial Farmers' Willingness to Adopt Crop Insurance in Zimbabwe: A Case of Mazowe district

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Abstract: **As a result of frequent climatic hazards, crop insurance has become an effective risk mitigating tool in agriculture, ease immediate financial pressure of a poor harvest and prevent poor smallholder commercial farmers from getting poorer. This study examined the determinants of crop insurance adoption by Smallholder Commercial Farmers using farm-level data from Mazowe district in Mashonaland Central Province of Zimbabwe. Based on three wards which were selected purposively, 165 farmers were randomly selected and interviewed using self-administered questionnaires. The double hurdle model was employed, based on 150 farmers who reported to be growing similar crops, which are maize, tobacco and soya-bean. Econometric results of the double-hurdle model revealed that income, subsidies, knowledge on crop insurance,, perception on risk, farm size, farming experience and education positively influence crop insurance adoption and extent of adoption by smallholder commercial farmers. On the other hand, the results also reveal that age negatively influence the adoption and extent of adoption of crop insurance. Thus, policy interventions that aim to increase crop insurance adoption by farmers such as involuntary insurance coverage for farmers that receive inputs on credit from the government are required. Furthermore, insurance scheme providers and agricultural extension agents should add more effort in undertaking awareness campaigns and education about the benefits of crop insurance and assist farmers on any aspect of crop insurance.**

Keywords: **Smallholder Commercial Farmers, Crop insurance, Double-hurdle model.**

I. INTRODUCTION

Crop insurance is considered to be an effective risk management tool in farming (Tsikirayi *et al*., 2013). It reduces the effects on farmers of adverse outcomes arising from climatic and other natural hazards. When insured risk occurs, Smallholder Commercial Farmers (SHCFs) get reimbursed a portion of their upfront investment, thereby easing the immediate financial pressure of a poor harvest (Masara and Dube, 2017). Without crop insurance, the occurrence of climatic hazards makes poor SHCFs poorer. Therefore, it is a reasonable expectation that SHCFs would seek to cushion themselves against the risks inherent in agricultural production through purchasing crop insurance. However, despite the high risks inherent in agricultural activities and farmers being perceived to be risk averse, a very low percentage of farmers in Mazowe district actually purchase crop insurance policies and of those that do, the extent of insurance coverage is similarly low. Sample evidence shows that only 32 per cent of the SHCFs in Mazowe district have crop insurance. It therefore becomes an issue of research curiosity and matter of policy concern as to why? Answers to this question can be derived from an investigation of factors that determine smallholder farmers' decision to participate in crop insurance and extent of coverage purchased.

II. BACKGROUND OF THE INSURANCE IN ZIMBABWE

The insurance industry in Zimbabwe is fairly diversified and there are 629 registered entities in the non-life insurance industry and 20 of these are insurance companies (Insurance and Pensions Commission (IPEC), 2018). Out of the 20 insurance companies, approximately 6 insurance companies[1] offer crop insurance to farmers where the insurance contracts offered include insurance against hail, drought, barn fire among others and weather index insurance is one of the insurance products designed for small scale farmers. Agricultural insurance can be broadly classified into three main categories based on how claims are determined and these include Indemnity-based, Index-based and Crop-revenue[2] based agricultural insurance (Iturrioz, 2009). In Zimbabwe, indemnity-based and index-based are the most issued products and crop insurance, in particular-tobacco hail insurance is the most purchased cover, contributing the highest percentage to the agricultural insurance portfolio. Among the cash crops grown in Zimbabwe which include tobacco, maize and soya-bean, maize and soya-bean are rarely insured as they are perceived to be low risk crops. However, despite tobacco being the highest risk and most insured crop, there is limited uptake of tobacco-hail insurance among

[1] These crop insurance companies include Alliance Insurance Company, Old Mutual Insurance Company, Zimnat Insurance Lion Company, Nicoz Diamond Insurance Company, Cell Insurance Company and Sanctuary Insurance Company.

[2] Claim payment on Indemnity-based insurance products is based on the actual loss incurred by the policy holder while index-based insurance products pays out claims based on index measurement (an objectively observable variable that is highly correlated with production losses and cannot be influenced by the insured such as rainfall, temperature, regional yield and river levels) and not on the actual loss incurred in the field (Iturrioz, 2009; Tsikirayi *et al*., 2013). Crop revenue agricultural insurance protects the insured farmer against the consequences of low prices, low yields or combination of both (Iturrioz, 2009).

SHCFs. Whether this can be attributed to insurance related, socio-economic and farm-specific factors as suggested by Branstrand and Wester (2014), Wairimu *et al*. (2016) and Velandia *et al*. (2009) is subject to investigation since determinants of crop insurance participation are diverse and not altogether obvious.

Prior the Fast Track Land Reform Programme (FTLRP) of 2000, agricultural insurance companies mainly focused on Large Scale Commercial Farmers (LSCFs) and SHCFs for they possessed high value equipment that required to be insured. Post the FTLRP, a new breed of LSCFs and SHCFs emerged, making agricultural insurance companies reconsider the conditions and criteria for quality delivery of agricultural insurance. Farming and insurance knowledge, experience, management skills and property ownership of the newly resettled farmers was minimal compared to the previous landowners, making it risky to insure these farmers (Tsikirayi *et al*., 2013). Thus, after the FTLRP, the number of insured farmers dropped significantly. Although the Government of Zimbabwe tried to help these new farmers with subsidies in the form of agricultural inputs and farm implements, this created the dependency syndrome. Maybe, Government programmes to support SHCFs, for example, the Presidential Input Schemes and Operation Maguta negatively influenced crop insurance adoption by farmers since a loss incurred while using Government inputs (a subsidy) has less impact on farmer's welfare compared to a production loss incurred by the farmer while using own farm inputs. Thus, the FTLRP brought dramatic changes to the agricultural sector, where the poor resettled farmers occupied vast amounts of land with dire implications on the agricultural insurance industry.

Although SHCFs are generally perceived to be risk averse and strive to reduce risk, the uptake of crop insurance has remained very low (Tsikirayi *et al*., 2013). Insurance and Pension Commission (IPEC) (2018) noted that agricultural insurance, including that of hail, represented 1 per cent of the global market in 2016 whereas in 2010, this percentage amounted to 3 per cent. According to IPEC reports, from 2012 to 2013, the contribution of agricultural insurance to Gross Premium Written (GPW) increased by 22.61 per cent while in 2014 and 2015, GPW fell by 2.55 per cent and 29.19 per cent respectively and this indicates that the agricultural insurance could be declining. Although Zimbabwe is a predominantly agro-based economy, the relative contribution of agricultural insurance premium to gross premium written is low and this does not commensurate with high level of contribution of agriculture to gross domestic product. The research issue is that farmers have not made an initiative to participate in crop insurance despite being perceived to be risk averse and the benefits of crop insurance in the event of a climatic hazard. Crop insurance has a huge potential for development of the agricultural sector and the economy at large through the creation of backward and forward linkages between sectors. It is against this backdrop that this study seeks to examine the determinants of smallholder commercial farmers' decision to participate and the extent of their participation in crop insurance. More specifically, this research has two objectives:

- To identify factors influencing smallholder commercial farmers' crop insurance participation.
- To identify factors influencing smallholder commercial farmers' extent of participation in crop insurance.

That is, this research identify the key issues that accounts for the limited uptake and greater variability in crop insurance adoption. Knowledge of the likelihood of farmers choosing not to purchase crop insurance would enable policy makers to formulate and implement appropriate policy responses that promote the purchase of insurance among SHCFs.

III. LITERATURE REVIEW

Various theories exist in explaining the factors influencing the adoption of crop insurance by farmers. For example, the theory of asymmetric information pioneered by George Akerlof (1970), Michael Spence (1973) and Joseph Stiglitz (1976) highlight that information asymmetry is of importance in impeding uptake of crop insurance by farmers. Asymmetric information is a situation in the market where an agent on one side of the market has more information that is key to the economic relationship which the other agent does not possess. In the case of Mazowe district, knowledge on insurance by farmers might be an importance factor for they are located in a remote area. In addition to theory of asymmetric information, the Expected Utility Theory (EUT) suggest that a SHCF's decision to purchase or not to purchase crop insurance depends on the joint action/event combination that maximise his or her expected utility, while information economics suggest that some SHCFs might fail to purchase crop insurance due to the presence of asymmetric information in the agricultural insurance markets.

Empirical investigations have been conducted by previous studies using different approaches in the domain of panel data, cross sectional data, double hurdle model, probit and logit models. Several studies used logit and probit models[3] (Ginder *et al*., 2009; Branstrand and Wester, 2014; Jin *et al*., 2016; Fahad *et al*., 2018; Masara and Dube, 2017; Wang *et al*. , 2016) while others used multinomial logit and multinomial probit models[4] (Velandia *et al*., 2009; Goodwin and Mishra, 2003; Kumari *et al*., 2017) in examining the decision to purchase crop insurance and these models are intended to answer the question: what determines the decision to participate in crop insurance? For example, Velandia *et al*. (2009) employed the multinomial probit model to examine factors influencing farmers' adoption of crop insurance, forward contracting and spreading sales in the United States of America. The results revealed that farmers with low off-

[3] In the logit and probit models, the decision to participate in crop insurance is treated as a binary variable.

[4] In the multinomial probit and multinomial logit models, the decision to adopt crop insurance is treated as a multi-response variable.

farm income tend to use crop insurance and proportion of owned acres, off-farm income, education and age were found to affect the adoption of risk management tools.

In Sweden and using cross sectional data, Branstrand and Wester (2014) investigated the determinants of crop insurance adoption by farmers using logit model and the study found that farmers with large land size are more likely to purchase crop insurance while age, education and off-farm income were found to have no impact on crop insurance purchase decision, contrary to Velandia *et al*. (2009) findings.

In a bid to investigate the effect of farmers' risk preferences on their decisions to purchase agricultural weather index insurance in China, Jin *et al.* (2016) used the binary logistic regression model and found that farmers' risk aversion, farmers' subjective beliefs on the probability of crop losses, farming experience, education, farm size positively affect the probability of the decision to buy weather index-based crop insurance while household income was found to negatively influence the decision to buy weather index-based crop insurance. In an attempt to seek factors influencing farmers' crop insurance participation over time in China, Wang *et al*. (2016) employed the logit model and used a four year short panel data for the period 2007-2010. The results of the study revealed dynamic changes in the factors affecting farmers' crop insurance decision, reflecting gradual adaptation of crop insurance program overtime. With time, crop insurance uptake was influenced by yield volatility, education, and engagement experience and farm size.

Masara and Dube (2017) analysed socio-economic factors influencing uptake of agricultural insurance by smallholder maize farmers in Zimbabwe using logit model. The results revealed that age, total income, education and farmers receiving advice about insurance positively influenced uptake of agricultural insurance while farming experience and total land size negatively influenced uptake of agricultural insurance. A similar study in Zimbabwe by Tsikirayi *et al*. (2013) used descriptive statistics which may be a pre-cursor to future research but however, descriptive studies cannot be used to correlate variables or determine causal effect, hence descriptive results are unreliable and unscientific.

Ellis (2016) examined the willingness to pay for crop insurance among cereal farmers in the Eastern region of Ghana. Using the probit model to estimate the mean willingness to pay for crop insurance, study found education level, farming experience, extension service, and weather variation, aware of crop insurance to be negatively related with willingness to pay for crop insurance while income and borrowing was positively related with willingness to pay for crop insurance.

Besides using these probit and logit models, some studies used the double hurdle model. For example, Wairimu *et al.* (2016) investigated factors affecting adoption of weather index-based crop insurance in Kenya and the results revealed that access to extension, education level and perception had positive effect on adoption of weather index-crop insurance while farming experience, age, size of cultivated land, distance to agricultural offices and distance to extension agent office negatively influenced adoption of weather index-based insurance.

Danso-Abbeam *et al*. (2014) employed the independent double hurdle model to determine factors influencing farmer's adoption of cocoa price insurance and the premium they are willing to pay in the Ghana. Probit regression results revealed that farmer's interest in cocoa price insurance was positively influenced by marital status, education level, farming experience, farm size, farm age and income and negatively influenced by household size. Premiums that farmers are willing to pay were positively influenced by marital status, education, income from cocoa farm and awareness of insurance scheme.

In Ghana, Okoffo *et al*. (2016) assessed the factors affecting willingness to pay for crop insurance and insurance companies' willingness to provide crop insurance to cocoa farmers using the double hurdle model. The study found that age, marital status and education positively influenced cocoa farmers' willingness to insure their farms while household size and cropped area negatively influence farmers' willingness to insure their farms. In addition, age, household size and cropped area was found to positively influence the premium cocoa farmers are willing to pay while marital status and cocoa income negatively influence premium farmers are willing to pay.

Although probit, logit, multinomial probit models have been used by many previous studies, these models were inappropriate to use since they do not capture the extent of adoption of crop insurance. Despite farmer's decision being limited to either adopt or not adopt insurance, this does not mean that only probit and logit models are more appropriate as used by most of the previous research. These models are the most popular and used by most previous research, but however, the biggest shortcoming of these models is that they do not measure the extent of participation in crop insurance since they treat insurance participation as a one-step procedure (Wairimu *et al*., 2016). Due to the short comings of these models, several better models exist such as the double hurdle model.

This study characterise the adoption decision as a sequential two-step decision process; (a) the decision to purchase (participation decision) crop insurance and (b) the amount of insurance (extent of participation decision) premium to pay, conditional on the first decision. The study used the double hurdle model as the appropriate empirical procedure to capture both the determinants of SHCFs' crop insurance participation and extent of participation as used by Wairimu *et al.* (2016), Danso-Abbeam *et al*. (2014) and Okoffo *et al*. (2016). The double hurdle model is a better model for modelling farmers' insurance adoption decision because it captures both the decision to adopt and the extent of adoption of crop insurance.

Several factors that influence participation and extent of participation in crop insurance can be classified into insurance related, socio-economic factors and farm-specific factors as used by previous studies. The proxy variables for insurance related factors are knowledge on insurance, access to credit and satisfaction with insurance (Kumari *et al*., 2017; Masara and Dube, 2017). Socio-economic factors include age, household size, education, off-farm income, and perception on risk while farm-specific factors include farm size, farming experience, income from farming and subsidies (Masara and Dube, 2017; Wairimu *et al*., 2016; Jin *et al*., 2016; Branstrand and Wester, 2014; Danso-Abbeam *et al*., 2014).

3.1 Theoretical Framework

The Expected Utility framework is the work horse or generally accepted approach to the analysis of decision making under risk and uncertainty that has been used to model farmers' decisions regarding the adoption of crop insurance. This conceptual framework has been used by previous related studies such as studies by Wairimu *et al*. (2016), Branstrand and Wester (2014) and Velandia *et al*. (2009). Stated in its simplest form, let $[E] = E_i\,; i = 1 \dots N$ represent a vector of uncertain events which can occur with a known probability p or an unknown probability π. The former is a case of risk while the latter is a case of uncertainty. Also let $[A] = a_j\,; j = 1 \dots J$ represent the actions open to a decision maker facing the uncertain events in E. Each combination $[a_j|E_i]$ yields an outcome $q_{ij} = q(a_j|E_i)$ on which the decision maker's payoff (u_{ij}) or utility can be defined by a utility function $u = u(q_{ij})$.

The SHCF's utility cannot be observed, but instead observe the decision made, which is likely to be affected by insurance related, socio-economic and farm-specific factors. We assume that the SHCFs' utility function can be represented by von Neumann-Morgenstern expected utility function:

$$E[u(q_{ij}) = \sum_{i=1}^{N} p_i\,(q_{ij}) \qquad (1)$$

when probabilities of occurrence of risk events are known and Savage subjective utility function:

$$E[u(q_{ij}) = \sum_{i=1}^{N} \pi_i\,(q_{ij}) \qquad (2)$$

in the case where probabilities of occurrence on uncertain events are not known (Cowell, 2006; Gravelle and Rees, 2004) .

The possible states of nature facing smallholder farmers in the Mazowe district arise mainly from natural and climatic hazards. For simplicity of exposition, we limit analysis to tobacco and the uncertain events of hail storms and barn fire occurrence. We also assume that the only actions open to SHCFs is to either insure or not to insure their tobacco crop. Let π_{hf} and π_{nhnf} represent the farmer's subjective probabilities of the occurrence of these natural hazards, where $\pi_{hf} + \pi_{nhnf} = 1$. The outcomes $q(.)$ are as illustrated in the payoff matrix below:

Table 1: Illustrative Payoff Matrix for Farmer's Decision Making under Risk and Uncertainty

Action	State of Nature	
↓	Hail (H) Barn Fire (F) (π_{hf})	No Hail (NH) No Barn Fire (NF) $\pi_{nhnf} = (1-(\pi_{hf})$
Insure tobacco(a_I)	$q(a_I\|HF)$	$q(a_I\|NHNF)$
Don't Insure (a_{DI})	$q(a_{DI}\|HF)$	$q(a_{DI}\|NHNF)$

Thus, the expected utility of insuring the tobacco crop against hail and barn fires can be represented as:

$$E[uq(a_I|HF)] = \sum_{i=HF}^{NHNF} \pi_i\, q(a_j|E_i) = \pi_{hf}\,q(a_I|HF) + (1-\pi_{hf})q(a_I|NHNF) \qquad (3)$$

Similarly, the expected utility of not insuring the tobacco crop is

$$E[uq(a_{DI}|NHNF)] = \sum_{i=HF}^{NHNF} \pi_i\, q(a_j|E_i) = \pi_{hf}\,q(a_{DI}|HF) + (1-\pi_{hf})q(a_{DI}|NHNF) \qquad (4)$$

If $E[uq(a_I|HF)] > E[uq(a_{DI}|NHNF)]$, the farmer will buy crop insurance; otherwise not.

The difference between the expected utility with crop insurance and without crop insurance are the potential factors influencing the decision on whether to adopt crop insurance. Denote the expected utility with crop insurance by U_q^I, that is $E[uq(a_I|HF)] = U_q^I$ and denote the utility without crop insurance by U_q^{DI}, that is $E[uq(a_{DI}|NHNF)] = U_q^{DI}$.

The farmer will decide to adopt crop insurance if the difference between the expected utility with insurance and the expected utility without crop insurance is greater than zero $(\hat{C}^D > 0)$; where $\hat{C}^D = (U_q^I - U_q^{DI})$. The difference, $\hat{C}^D$ is an unobserved latent variable but the adoption decision (Y_c) is observable such that:

$$Y_c = \begin{cases} 1 \ if \ \hat{C}^D > 0 \\ 0 \ if \ \hat{C}^D \leq 0 \end{cases} \qquad (5)$$

Where $Y_c = 1$ if the farmer adopt crop insurance and $Y_c = 0$, otherwise.

The derivation of equation (5) makes it empirically easy to determine factors influencing the adoption of crop insurance. The action taken by the SHCFs, on whether to participate in crop insurance and the extent of participation depends on insurance related, socio-economic and farm specific factors which might influence the individual farmer's risk preferences; which is captured by the shape of $u\,(.)$, the farmer's utility function. These factors consequently affect the value of the unobserved latent variable $\hat{C}^D$ and the decision of whether or not to adopt crop insurance.

This study used the double hurdle model as used by Wairimu *et al*. (2016) where in the first hurdle, the probit model was used to determine the likelihood that a farmer purchase crop insurance and in the second hurdle, the Tobit model was used to determine the extent of participation. The first equation relates to the decision on whether to participate(y) expressed as follows:

$$y_c = 1 \ if \ \hat{C}^D > 0 \ and \ 0 \ if \ \hat{C}^D \leq 0$$

$$\hat{C}^D = z_i^{'}\alpha + \nu_i \qquad \text{Participation equation} \qquad (6)$$

Where $\hat{C}^D$ is a latent endogenous variable describing SHCFs' decision to participate in crop insurance, $z_i^{'}$ is a vector of factors explaining participation decision derived from empirical literature such as those by Wairimu *et al*. (2016) and Branstrand and Wester (2014), ν_i is the error term of the first hurdle and α is a vector of parameters of the first hurdle. If $y_c = 1$, then $\hat{C}^D > 0$ and the individual is maximising utility by participating in crop insurance.

The second hurdle which closely represent the Tobit model is expressed as follows:

$$t_i = \left(x_i^{'}\beta + \varepsilon_i \quad if \ \min(x_i^{'}\beta + \varepsilon_i \ ; z_i^{'}\alpha + \nu_i) > 0 \right. \qquad (7)$$

$$0 \ otherwise$$

$$t_i^* = x_i^{'}\beta + \varepsilon_i \qquad \text{Expenditure equation} \qquad (8)$$

Where t_i^* is a latent endogenous variable describing SHCFs' decision to purchase crop insurance, t_i is an observed depended variable (SHCFs' expenditure on crop insurance), $x_i^{'}$ is a vector of factors explaining expenditure decision, ε_i is the error term of the second hurdle and β is a vector of parameters of the second hurdle. The respective error terms, ν_i and ε_i are assumed independent and distributed as $\nu_i \sim N(0,1)$ and $\varepsilon_i \sim N(0, \sigma^2)$, otherwise, the model is not identified.

The empirical adoption model estimated in the first hurdle (Probit model) was expressed as follows:

$$Part_i = \beta_0 + \beta_1 Age_i + \beta_2 FarmExp_i + \beta_3 FarmSz_i + \beta_4 Educ_i + \beta_5 AccessCrd_i + \beta_6 Income_i + \beta_7 KnowInsur_i + \beta_8 PercepRisk_i + \beta_9 Subsidies_i + \varepsilon_i \qquad (9)$$

The dependent variable $Part_i$ refers to whether a SHCF i adopted crop insurance and was dichotomous. The covariates are described in Table 1. The extent of adoption empirical model (Tobit model) for the second hurdle was expressed as follows:

$$Extent_i = \alpha_0 + \alpha_1 Age + \alpha_2 FarmExp_i + \alpha_3 FarmSz_i + \alpha_4 Educ_i + \alpha_5 AccessCrd_i + \alpha_6 Income_i + \alpha_7 KnowInsur_i + \alpha_8 PercepRisk_i + \mu_i \qquad (10)$$

The dependent variable in the second hurdle refers to the amount of insurance premium per hectare paid by the SHCF i. The description of explanatory variables used is shown in Table 1. The coefficients of the double hurdle model are estimated using Maximum likelihood estimation procedure and cannot be interpreted in the usual way as in the linear regression model. Therefore, marginal effects were computed to assess the impact of regressors on the dependent variable.

Table 2: Description, measurement and hypothesised effects of the variables in the model

Variables	Description of variables	Sign	Hypothesised Effect
Adopt	Whether SHCF adopted crop insurance		
Extent	Amount of insurance premium paid per hectare (dollars)		
FarmSz	Area under cultivation in hectares	+	Farmers with larger area under cultivation engage in large scale investments and have higher risk exposure, thus tend to adopt crop insurance more often. In addition, farmers with large land under Cultivation have greater wealth, higher capital availability and greater risk exposure (Wairimu *et al*., 2016).
Educ	Farmer's years of schooling	+	Higher education increases the ability to use risk management tools such as crop insurance and better educated farmers are believed to be more risk averse, thus are more willing to adopt crop insurance. Low levels of education is likely to be associated with negative perception on crop insurance, hence impede high uptake of crop insurance.
Age	Age of the farmer in years	+/-	Older farmers have higher level of experience in farming than young farmers and they desire to continue with their traditional risk management tools in farming. However, young farmers have low income and wealth, limited access to credit and thus less likely to adopt crop insurance
Subsidies	Value of command agricultural inputs received by the farmer	-	When farmers receive inputs from the government, a loss due to a climatic hazard does not have much impact on farmer's welfare when compared to a farmer who uses own farm inputs and since the command agricultural programme does not

			force farmers to purchase insurance, SHCFs are reluctant to adopt crop insurance.
FarmExp	Farming experience in years	+	Farming experience encourages the adoption of improved technologies and makes it easier to identify best risk management tools such as crop insurance to avoid income loss since they have been exposed to risk and uncertainty in the past
AccessCrd	Access to credit (1=Yes, 0=No)	+	Access to credit enables access to the required farm inputs and some farmers that avail loans from banks compulsorily come under insurance coverage. In addition, farmers that avail farm inputs on credit from contracting companies are encouraged to be under insurance coverage by those companies, thus promoting insurance adoption for farmers with access to credit.
PercepRsk	Perceived yield risk (0=high, 1=moderate, 2=neutral, 3=low risk, 4=no risk)	+	Farming is subjected to greater risk of weather, pests and diseases and farmers that perceive a higher level of farming risk are more willing to purchase crop insurance compared to farmers that perceive no farming risk (Branstrand and Wester, 2014).
Knowledge	Knowledge on crop insurance (1=Yes, 0=No)	+	Theory of asymmetric information argue that when one side of the market is more informed than the other, in the extreme case, no transaction might take place and asymmetric information limit uptake of crop insurance
Income	Total income in dollars (0= Income≤$4000, 1=$4000<Income≤$8000, 2=$8000<Income≤$12000, $12000<Income	+/-	Higher incomes levels can be used to manage production risk and makes crop insurance affordable, thus promoting adoption of crop insurance. However, higher total income is generally regarded as a proxy for risk aversion and farmers with higher income levels tend to be less risk averse, which impede adoption of crop insurance.

3.2 Sampling and data collection

A sample of 165 SHCFs was obtained through the use of Cochran's (1977) formulae. However, only 150 respondents who were growing all the main crops being grown by almost every farmer, which are maize, tobacco and soya-bean were used in the study. The sample comprised of 49 adopters and 101 non-adopters of crop insurance and these adopted only crop insurance for tobacco. The sample was selected randomly from three wards with a population of approximately 1322 farmers out of 35 wards in Mazowe district with a population of approximately 36 786 farmers. Pre-tested open-ended and closed-ended questionnaires were used to collect primary data from SHCFs in Mazowe district during the period 12 February 2019 to 2 March 2019. Questionnaires with open-ended questions and closed ended questions were used to collect cross-sectional data about SHCFs' socio-economic, insurance related and farm-specific characteristics postulated to have an influence on the adoption of crop insurance.

IV. EMPIRICAL RESULTS

4.1 Descriptive statistics results

Table 2 presents the descriptive statistics on socio-economic and farm-specific characteristics of sampled SHCFs. On average, a SCHF was paying an insurance premium of $76 per hectare. The average age and farming experience of a SHCF was approximately 46 years and 17 years, respectively. The average area under cultivation was approximately 13 hectares. The average value of command agricultural inputs received by SHCF was approximately $1014 while the average years of education of a SHCF was approximately 11 years. The coefficient of variation for insurance premium, farm size and subsidies was very high, indicating that most of the farmers paid insurance premium, cultivated hectares of land and received inputs of value significantly below and/ above the mean.

Table 3: Distribution of the SHCFS by continuous variable

Variable	Mean	Coeff. Var	Std. Dev.
Insurance Premium	75.94	1.81	137.31
Age of SHCF	46.45	0.29	13.67
Experience	16.58	0.60	9.91
Farm Size	13.22	1.35	17.79
Education	10.62	0.38	3.98
Subsidies (Value)	1014.82	2.78	2816.29

The coefficient of variation for age of the SHCF, farming experience and education was low, indicating that the age, farming experience and education level of most SHCFs was significantly close to the mean. Out of 165 interviewed SCHFs, only 150 SHCFs reported that they were growing major crops in the area, which are maize, tobacco and soya-bean.

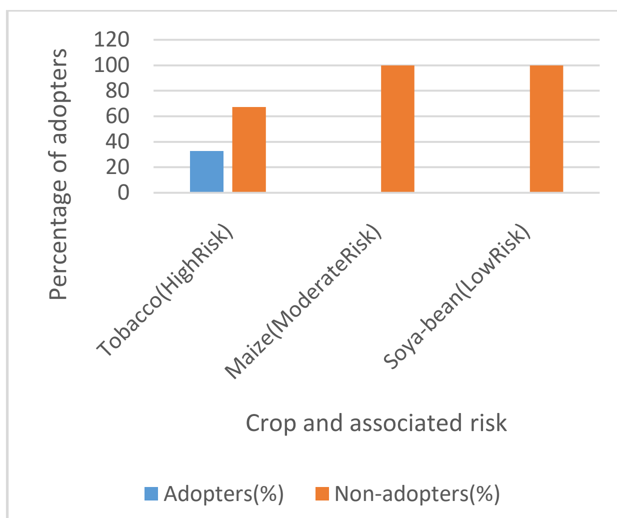

Figure 1: Distribution of SHCF insurance adoption across crops

From the 150 SCHFs, none was found to have crop insurance for maize and soya-bean, indicating 100 per cent crop insurance non-adoption for maize and soya-bean. Tobacco was found to be the only insured crop, where approximately 33 per cent adopted crop insurance for tobacco although it was indicated to be the highest risky crop.

Table 4: Distribution of the SHCFs by their major reason for satisfaction with crop insurance

Reason	Frequency	Per cent
Probability of receiving claim payment is low	69	46
Probability of receiving claim payment is high	10	6.67
Risk is covered	71	47.33
Total	150	100

From the 150 interviewed SHCFs, the aforementioned reasons for crop insurance adoption or non-adoption were the most cited by farmers. Only 6.67 per cent of the farmers who were satisfied with crop insurance indicated that the probability of receiving claim payment is high while 47.33 per cent of the farmers who were satisfied with crop insurance were basing on the argument that risk in farming was covered. The results also indicate that 46 per cent of the SHCFs were not satisfied with crop insurance because the probability of receiving claim payment is low.

Table 5: Distribution of the SHCFs by knowledge about crop insurance

Knowledge on insurance	Freq.	Percent
No knowledge about insurance	84	56
Has knowledge about insurance	66	44
Total	150	100

The descriptive statistics in table above shows that the majority 56 per cent had no knowledge about crop insurance while 44 per cent indicated that they had knowledge about crop insurance

4.2 Estimation of the double hurdle model

Table 5 below summarises the double hurdle model results. The parameter estimates of the double hurdle model provide the direction and not probability or magnitude of change. Thus, only signs of the estimated coefficients are interpreted. The results of the estimated participation equation (probit) of the double hurdle model shows a positive coefficient of education and experience implying that farmers with higher education and more years of farming experience are more likely to adopt crop insurance compared to farmers with lower education and less years of experience.

Table 6: Double hurdle Model on factors influencing SHCFs' willingness to adopt and pay for crop insurance Probit Model: Willingness to adopt crop insurance (Participation equation)

Insurance	Coef.	Robust Std. Err.	z	P>z	[95% Conf. Interval]	
Age	-0.1677	0.0242	-6.94	0.0000	-0.2151	-0.1204
FarmExp	0.1111	0.0208	5.33	0.0000	0.0703	0.1520
FarmSz	-0.0156	0.0053	-2.94	0.0030	-0.0260	-0.0052
Educ	0.3804	0.0401	9.5	0.0000	0.3019	0.4589
AccessCrd						
Access to credit	0.4211	0.2849395	1.48	0.1390	-0.1374	0.9795
Income						
$4K<Income=$8K	5.8287	0.2023	28.82	0.0000	5.4323	6.2252
$8K<Income=$12K	-1.1022	0.6698	-1.65	0.1000	-2.4150	0.2106
$12K<Income	5.1919	0.2543	20.42	0.0000	4.6935	5.6904
KnowInsurance						
KnowledgeInsur	-1.1595	0.2520	-4.6	0.0000	-1.6534	-0.6657
PercepRisk						
Moderate	-3.0769	0.3087	-9.97	0.0000	-3.6819	-2.4719
Neutral	-4.0570	0.4364	-9.3	0.0000	-4.9124	-3.2016
LowRsk	-7.4672	0.3562	-20.96	0.0000	-8.1653	-6.7692
NoRsk	-5.6962	0.3130	-18.2	0.0000	-6.3098	-5.0827
Subsidies	0.0005	0.00004	11.99	0.0000	0.0004	0.0005
_cons	294.7234	0.6832936	431.33	0.0000	293.3842	296.0627

Lnsigma						
_cons	3.7622	0.0233	161.27	0.0000	3.7165	3.8080
/sigma	43.0431	1.0041			41.1193	45.0569

***Significant at 1% level of significance. **Significant at 5% level of significance. *Significant at 10% level of significance.

Tobit Model: Extent of adoption of crop insurance (Quantity equation)

Insurance	Coef.	Robust Std. Err.	z	P>z	[95% Conf. Interval]	
Age	-0.3539	0.0905	-3.91	0.0000	-0.5312	-0.1766
FarmExp	0.7261	0.0643	11.29	0.0000	0.60000	0.8521
FarmSz	0.9986	0.1014	9.85	0.0000	0.7999	1.1974
Educ	0.4059	0.2582	1.57	0.1160	-0.1002	0.9120
AccessCrd						
Access to Credit	2.2899	1.6393	1.4	0.1620	-0.9231	5.5029
Income						
$4K<Income=$8K	18.0438	1.738621	10.38	0.0000	14.6361	21.4514
$8K<Income=$12K	21.4989	6.2405	3.45	0.0010	9.2679	33.7300
$12K<Income	16.8192	3.7801	4.45	0.0000	9.4104	24.2279
KnowInsurance						
KnowInsur	49.5778	2.8698	17.28	0.0000	43.9531	55.2026
PercepRisk						
Moderate	-47.5874	5.2839	-9.01	0.0000	-57.9437	-37.2312
Neutral	-76.8176	4.9664	-15.47	0.0000	-86.5515	-67.0836
LowRsk	-89.8221	4.8297	-18.6	0.0000	-99.2882	-80.3560
NoRsk	-88.0973	4.5474	-19.37	0.0000	-97.0100	-79.1846
_cons	62.1222	5.3051	11.71	0.0000	51.7244	72.5200

***Significant at 1% level of significance. **Significant at 5% level of significance. *Significant at 10% level of significance

The coefficient of knowledge on insurance in the participation equation was negative while the analogous coefficient in the quantity equation had a positive value, implying that farmers with knowledge on crop insurance are less likely to adopt crop insurance compared to farmers without knowledge on crop insurance but if they adopt crop insurance, they tend to pay higher insurance premium per hectare than farmers without knowledge on crop insurance. The coefficient of age in both the participation equation and quantity equation had a negative, implying that older farmers are less likely to adopt crop insurance compared to young farmers. The coefficient of education in the participation equation was positive while the analogous coefficient in the quantity equation was insignificant implying that farmers with more years of education are more likely to adopt crop insurance but there is no significant difference in insurance premium paid between farmers with more years of education and less years of education. The coefficient of perception on risk in both the participation equation and quantity equation was negative, implying that farmers who perceive risk to be low are less likely to adopt crop insurance and they pay low insurance premium compared to farmers who perceive risk to be high.

The coefficient of farm size in the quantity equation had a positive value while the analogous coefficient in the participation equation had a negative value. This implies that SHCFs with large land under cultivation are less likely to adopt crop insurance, but if they adopted crop insurance, they tend to pay higher premiums per hectare compared SHCFs with smaller land size under cultivation. The coefficient of farming experience in both the participation equation and quantity equation had a positive value, implying that farmers with more years of farming experience are more likely to adopt crop insurance and they pay a higher insurance premium per hectare compared to farmers with less years of farming experience. In both the participation equation and quantity equation, income had a positive coefficient implying that, farmers with higher income from agriculture are more likely to adopt crop insurance and they pay higher insurance premium compared to farmers with less income from agriculture. Subsidies had a positive coefficient implying that farmers who receive higher valued inputs from the government through the command agriculture program are more likely to adopt crop insurance.

All the factors were found to be statistically significant at 1 per cent and influence both the adoption and extent of adoption of crop insurance with the exception of access to credit. Naturally, coefficients of the double hurdle model are difficult and meaningless to interpret, hence it is important to find marginal effects.

Table 7: Marginal effects results

	dy/dx	Delta-method Std. Err.	z	P>z	[95% Conf.	Interval]
Age	-1.4649	0.1559	-9.3900	0.0000	-1.7705	-1.1593
FarmExp	1.4091	0.1414	9.9700	0.0000	1.1320	1.6863
FarmSz	0.7845	0.1019	7.7000	0.0000	0.5849	0.9842
Educ	2.9680	0.2900	10.2300	0.0000	2.3996	3.5364
AccessCrd						
Access to credit	4.8987	2.4003	2.0400	0.0410	0.1942	9.6033
Income						
$4K<Income=$8K	40.6242	1.9506	20.8300	0.0000	36.8011	44.4474
$8K<Income=$12K	21.4242	6.2147	3.4500	0.0010	9.2436	33.6047
$12K<Income	33.5512	3.6069	9.3000	0.0000	26.4818	40.6207
KnowInsurance						
knowledgeInsur	33.9044	3.1416	10.7900	0.0000	27.7470	40.0618
PercepRisk						
Moderate	-73.6299	5.4756	-13.4500	0.0000	-84.3620	-62.8979
Neutral	-104.8299	4.9846	-21.0300	0.0000	-114.5994	-95.0603
LowRsk	-119.7151	4.7890	-25.0000	0.0000	-129.1014	-110.3287
NoRsk	-117.1042	4.5217	-25.9000	0.0000	-125.9665	-108.2418
Subsidies	0.0032	0.0002	16.8700	0.0000	0.0028	0.0036

(*) dy/dx for factor levels is the discrete change from the base level.

From the marginal effects results, experience had a positive coefficient implying that an additional year of experience of a farmer is associated with an extra $1.41 of insurance premium per hectare. The results confirm the fact that higher farming experience makes it easier for farmers to identify effective risk management tools such as crop insurance, promoting the adoption of improved hedging tools (Wairimu *et al*., 2016). These results were consistent with the findings of Jin *et al*. (2016) in China who found that farming experience positively influence the decision to buy weather index-based crop insurance. The coefficient of farm size was positive, implying that an additional hectare under cultivation increases the amount of insurance premium per hectare paid by $0.79 and this corroborate the results of Kumari *et al*. (2017). The results of the study confirm that SHCFs have relatively small land sizes, limiting the amount of insurance premium per hectare to be paid and farmers with large farm size under cultivation tend to pay higher insurance premium per hectare.

Educational attainment was found to positively influence the amount of insurance premium paid per hectare, with each additional year of education increasing the amount of insurance premium per hectare paid by $2.97. The findings supports the results of Masara and Dube (2017) who found that education positively influence the uptake of agricultural insurance. Access to credit had a positive coefficient and the results of the marginal effects showed that farmers with access to credit pay insurance premium per hectare of $4.90 higher than insurance premium per hectare paid by farmers with no access to credit. The study confirm that farmers with access to credit are more likely to adopt and pay higher insurance premium compared to farmers with no access to credit as found by Ellis (2016). The results of the marginal effects on income showed that farmers with income category of $4000<Income≤$8000, $8000<Income≤$12000 and $12000<Income paid an insurance premium per hectare of $40.62, $21.42 and $33.55 higher than farmers with income of less than $4000, respectively. This implies that higher income positively influence the amount of insurance premium per hectare paid by the farmer, maybe because farmers with higher agricultural income are able to cover the cost of insurance and the higher the income from agriculture, the higher the probability to purchase crop insurance and the higher the insurance premium that farmers will be willing to pay. This was consistent with the findings of Danso-Abbeam *et al*. (2014)

Marginal effect of knowledge on crop insurance showed that farmers with knowledge on crop insurance paid insurance premium per hectare of $33.90 higher than farmers with no knowledge of insurance. The coefficient of perception on risk was negative, implying that farmers who perceive risk to be high pay higher insurance premium than farmers who perceive risk to be low. In addition, the results showed a positive relationship between the value of inputs from the government and amount of insurance premium per hectare paid by the farmer. Thus, an additional $1 value of inputs from the government increased the amount of insurance premium paid per hectare by $0.0032. The positive influence of subsidies on uptake of crop insurance was consistent with the results of Wang *et al*. (2016) in China.

V. SUMMARY AND CONCLUSIONS

This study examined the determinants of crop insurance adoption by smallholder commercial farmers using farm-level data collected from farmers in Mazowe district**.** The double hurdle model was employed to determine how insurance related, socio-economic and farm-specific factors affect the decision to purchase crop insurance by smallholder commercial farmers. Thus, the study estimated the impact of different factors on the likelihood of adoption and extent of adoption of crop insurance. Basing on the results of the double hurdle model, the econometric results showed that farming experience, income, years of education of the farmer, value of command agricultural inputs, knowledge on insurance, area under cultivation and access to credit positively influence the adoption and extent of adoption of crop insurance. However, age and perception on risk in farming negatively influence the adoption and extent of adoption of crop insurance.

VI. POLICY RECOMMENDATIONS

Based on the research findings, the study recommends policy makers to implement policy interventions that promote stimulation of knowledge on crop insurance and establish institutions that safeguard insured farmers from unscrupulous crop insurance companies. This can be done through awareness campaigns and education on crop insurance. Farmers should be encouraged to grow cash crops that improve farmers' agricultural income and higher agricultural income can improve the likelihood of adoption and extent of adoption of crop insurance because there are direct and indirect costs associated with adoption of crop insurance. In addition, farmers should commercialise their farming activities through the help of the government and non-governmental organisations, increasing engagements with markets and improve farm income. Since none of farmers was found to have insurance for maize, policies that promote universal insurance to maize farmers especially those who receive inputs on credit from the government should be implemented by policy makers to improve uptake of crop insurance.

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REFERENCES

[1] Akerlof, G.A., 1970. The market for "lemons": Quality uncertainty and the market mechanism. In *Uncertainty in economics* (pp. 235-251). Academic Press.

[2] Branstrand, F. and Wester, F., 2014. Factors Affecting Crop Insurance Decision: A Survey among Swedish Farmers. *Degree Project/SLU, Department of Economics*, (878).

[3] Cochran, W.G., 1977. *Sampling Techniques*. 2nd ed. New York: John Wiley & Sons.

[4] Cowell, A. F., 2006. *Microeconomics*:*Principles and Analysis*, 2nd edition, STICERD and Department of Economics, London School of Economics.

[5] Danso-Abbeam, G., Addai, K.N. and Ehiakpor, D., 2014. Willingness to pay for farm insurance by smallholder cocoa farmers in Ghana. *Journal of Social Science for Policy Implications*, *2*(1), pp.163-183.

[6] Ellis, E., 2017. Farmers Willingness to Pay for Crop Insurance: Evidence from Eastern Ghana. *International Journal of Agricultural Management and Development*, *7*(4), pp.447-463.

[7] Fahad, S., Wang, J., Khan, A.A., Ullah, A., Ali, U., Hossain, M.S., Khan, S.U., Huong, N.T.L., Yang, X., Hu, G.Y. and Bilal, A., 2018. Evaluation of Farmers' Attitude and Perception Toward Production Risk: Lessons from Khyber Pakhtunkhwa Province, Pakistan. *Human and Ecological Risk Assessment: An International Journal*, *24*(6), pp.1710-1722.

[8] Ginder, M., Spaulding, A.D., Tudor, K.W. and Randy Winter, J., 2009. Factors Affecting Crop Insurance Purchase Decisions by Farmers in Northern Illinois. *Agricultural Finance Review*, *69*(1), pp.113-125.

[9] Gravelle, H. and Rees, R., 2004.*Microeconomics*, 3rd edition, Prentice Hall, Pearson Education Limited. London.

[10] Insurance and Pensions Commission., 2018. Consumer Education News Letter. Harare.

[11] Iturrioz, R. 2009. *Agricultural Insurance*. Primer Series on Insurance, Issue 12, Nov 2009, The World Bank.

[12] Jin, J., Wang, W. and Wang, X., 2016. Farmers' Risk Preferences and Agricultural Weather Index Insurance Uptake in Rural China. *International Journal of Disaster Risk Science*, *7*(4), pp.366-373.

[13] Kumari, M., Singh, K.M., Sinha, D.K., Ahmad, N. and Mishra, R.R., 2017. Role of Socio-economic Variables in Adoption of Crop Insurance: A Discriminant Function Approach.

[14] Masara, C. and Dube, L., 2017. Socio-economic Factors Influencing Uptake of Agriculture Insurance by Smallholder Maize Farmers in Goromonzi District of Zimbabwe. *Journal of Agricultural Economics and Rural Development*, 3(1): 160-166

[15] Mishra, A.K. and Goodwin, B.K., 2003. Adoption of crop versus revenue insurance: a farm-level analysis.

[16] Okoffo, E.D., Denkyirah, E.K., Adu, D.T. and Fosu-Mensah, B.Y., 2016. A Double-hurdle Model Estimation of Cocoa Farmers' Willingness to Pay for Crop Insurance in Ghana. *SpringerPlus*, *5*(1), p.873.

[17] Spence, A.M., 1973. Job Market Signaling. *Quarterly Journal of Economics*, *87*(3), pp.355-374.

[18] Stiglitz, J.E., 1976. The theory of" screening," education, and the distribution of income. *The American economic review*, *65*(3), pp.283-300.

[19] Tsikirayi, C.M.R., Makoni, E. and Matiza, J., 2013. Analysis of the Uptake of Agricultural Insurance Services by the Agricultural Sector in Zimbabwe. *Journal of International Business and Cultural Studies*, *7*, p.1.

[20] Velandia, M., Rejesus, R.M., Knight, T.O. and Sherrick, B.J., 2009. Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward

Contracting, and Spreading Sales. *Journal of Agricultural and Applied Economics*, *41*(1), pp.107-123.

[21] Wairimu, E., Obare, G. and Odendo, M., 2016. Factors Affecting Weather Index-based Crop Insurance in Laikipia County, Kenya. *Journal of Agricultural Extension and Rural Development*, *8*(7), pp.111-121.

[22] Wang, M., Ye, T. and Shi, P., 2016. Factors Affecting Farmers' Crop Insurance Participation in China. *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, *64*(3), pp.479-492.