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Risk Optimality and, Subscription and Subscription Intensity of Weather Index Insurance: Application of T-MOTAD and Negative Binomial Double Hurdle Model

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Abstract

This study sought to analyze risk efficient income and examine its effect on subscription and subscription intensity of weather index insurance (WII). Data was obtained from food crop farmers who were randomly sampled from the Upper West Region; and further, the T-MOTAD and Negative binomial hurdle model were estimated to arrive at the study findings. The study fills methodological gap by estimating the negative binomial hurdle and Zero-inflated negative binomial models as advancement of the Poisson regression model. Further, AIC, BIC, Log-likelihood, rootogram as well as the Vuong test were employed to ascertain the empirical superiorities of the estimated models to the data set. Results show that the risk efficient plans' incomes of GHS9403.42 ($854.08) and GHS9835.10 ($893.29) are higher than that of the income of GHS7412.97 ($673.29) from the farmer's optimal plans. Also, about two-third of farmers have subscribed to the weather index insurance in the study area; for intensity of subscription, 0.39ha on average out of every hectare of land cultivated is covered with the weather index insurance. The negative binomial hurdle model showed empirical superiority for the fit of the data set. The farmer's decision to subscribe and their subscription intensity of the weather index insurance are significantly influence by age, sex, farm size, experience, education, insurance prompt payment, extension service, credit access and risk efficient income. It is recommended that farmers should adopt the risk efficient plan to earn higher income to be able to afford WII premium, as this will increase their subscription intensity.

Keywords

Risk optimality, Subscription intensity, weather index insurance, T-MOTAD, Negative binomial double hurdle model, food crops, Upper West region of Ghana.

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Introduction

In Ghana, the agricultural sector is dominated by smallholder farmers and is mostly rain-fed, characterized by production and climate risk (Abdul-Razak and Kruse, 2017). Traditionally, these smallholder farmers have informally managed both production and climatic risk in their own way, but this has always led to their incurring losses (Antwi, 2016). Ellis (2017) noted that the Government of Ghana and other stakeholders in the agricultural and insurance sector upon realizing this, piloted and implemented the weather index-based insurance in the Upper West Region. The weather index insurance policy covers food crops such as maize, millet, sorghum, soya bean and groundnut and uses climate indicators to predict losses to the farmer (Amponsah et al., 2018). This was done to give the farmers access to a market-based risk management policy that could cater for the risks that is beyond their control (GAIP, 2013). Despite the significance of the weather index insurance policy, its penetration level is still very low in the Upper West Region. The factors identified are lack of awareness, insurance prompt payment, lack of preferred attributes, and a key among them is the low income level of the farmers (Akinola, 2014; Fiala, 2017; Addey et al., 2020; Feng et al., 2021).

Udo et al. (2015) asserted that to increase the income level of farmers in the events of production risk, a risk optimum farm plan is required. A risk optimum farm plan can be an effective support policy for weather index insurance and serve as an effective channel for farm credit facilities and advisory services, as well as agricultural risk management intervention (Koufie, 2020; Dai et al., 2023). Therefore, this study bridges the literature gap by providing a rigorous empirical evidence to know the risk efficient income obtained from the risk optimum farm plan, subscription and subscription intensity of the weather index insurance and the interaction between the risk efficient income, subscription and subscription intensity of the weather index insurance. The study also bridges the methodological gap by making Poisson regression model as base model and compare it with advanced count models such as the negative binomial hurdle model, and the zero-inflated negative binomial model. The study went further to empirically test the three selected count models to see which one among them is the best fit model for the study, using Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Log-like hood ratio test, Vuong statistical test and a rootogram.

Materials and methods

Study area, sampling procedure and sample size

The study was conducted in the Upper West region of Ghana, and a multi-stage sampling technique was used to select the food crop farmers for the study. The first stage was to purposively select the Wa Municipality and Wa West district. The second stage involved grouping all the twenty-six (26) major farming communities in the selected districts and randomly selecting sixteen (16) out of the twenty-six (26) communities using the lottery method. At stage three, proportionate sampling was used to select the 64 percent subscribers and 36 percent non-subscribers from the 16 selected farming communities. At the end of the sampling proceedure, 450 food crop farmers constituting 287 subscribers and 163 non-subscribers became the sample for the analysis.

Data collection and analysis

A face-to-face interview was conducted using a structured questionnaire to obtain cross-sectional data from the 450 food crop farmers who decided to be part of the survey. The Data was analysed using R statistical software version 4.04 and LiPS software.

Empirical estimation of Target MOTAD model for the study

In the context of this study, to formulate the actual Target-MOTAD problem, we first analyse the LP problem of the study without including risk constraint in the model. This was done by maximizing the expected gross margin E(GM) of the decision variables (x_j) subject to resource constraint. In this study, we defined the decision variables (x_j) as hectares of land to be allocated to the various crop enterprises. The various crop enterprises used in this study were maize, groundnut, soya bean and sorghum as these are the major food crop enterprises produced in the study area (Dembele, 2018). Therefore, the optimum income obtained from the LP model now becomes the Target Income for the Target-MOTAD model. The Target-MOTAD is analysed by including a risk constraint into the LP model and setting the Target income. Therefore, mathematically the Target-MOTAD for this study is given as:

$$\text{Maximize: } E(GM) = c_1x_1 + c_2x_2 + c_3x_3 + c_4x_4 \quad (1)$$

Subject to: <u>Resource constraint</u>

$$a_{1,1}x_1 + a_{1,2}x_2 + a_{1,3}x_3 + a_{1,4}x_4 \leq b_1$$

(Land constraint) (2)

$$a_{2,1}x_1 + a_{2,2}x_2 + a_{2,3}x_3 + a_{2,4}x_4 \leq b_2$$

(Labour constraint) (3)

$$a_{3,1}x_1 + a_{3,2}x_2 + a_{3,3}x_3 + a_{3,4}x_4 \leq b_3$$

(Capital constraint) (4)

$$a_{4,1}x_1 + a_{4,2}x_2 + a_{4,3}x_3 + a_{4,4}x_4 \leq b_4$$

(Fertilizer Constraint) (5)

<u>Risk constraint</u>

$$\sum_{j=1}^{n} C_{rj}x_j + y_r \geq T \text{ ... where } r = 1 \dots m \quad (6)$$

$$\sum_{r=1}^{s} p_r y_r = \lambda \quad (7)$$

$$x_1, x_2, x_3, \dots \geq 0. \text{ (Non –negativity constraint)} \quad (8)$$

Where gross margin E(GM) of the decision variables (x_j) represent the difference between the total revenue and the total variable cost (which comprised of labor cost and inputs cost during the production season). x_1 = maize, x_2 = groundnut, x_3 = soyabeans, x_4 = sorghum ($a_{1,1}$, $a_{1,2}$, $a_{1,3}$ and $a_{1,4}$) are the hectares of land apportion to maize, groundnut, soya bean and sorghum respectively. ($a_{2,1}$, $a_{2,2}$, $a_{2,3}$ and $a_{2,4}$) represent the labor days (man-days) apportion to maize, groundnut, soya bean and sorghum.($a_{3,1}$, $a_{3,2}$, $a_{3,3}$, and $a_{3,4}$) represent the amount of capital (GHS) apportioned to maize, groundnut, soya bean and sorghum respectively. ($a_{4,1}$, $a_{4,2}$, $a_{4,3}$ and $a_{4,4}$) represent kg/hectare of fertilizer apportioned to maize, groundnut, soya bean and sorghum. Also, b_1 represent the total hectares of land available to the farmer, b_2 represent the total labor days(man-days) available to the farmer, b_3 represent the total capital (GHS) available to the farmer for production activity and b_4 represent the total amount of fertilizer (kg) available to farmer. (c_1, c_2, c_3 and c_4) is the gross margin obtain by maize, groundnut, soya bean and sorghum enterprises. T = the optimum income obtained from the LP model without risk constraint (Target gross margin). s is the total number of time period considered. C_{rj} is the expected gross margin of the j^{th} enterprise in the r time period or farming season. y_r is the deviation below the target income (T) in time period r. λ is the maximum amount of short fall in the gross margin permitted. Therefore, the model solution was feasible and risk efficient plans (II and III) were obtained.

Empirical model estimation for the count regression model

The study employed the count regression model to analyse the risk-efficient income and risk aversion levels of farmers with regard to their subscription and subscription intensity of weather index insurance. The count model comprises two component modelling processes. The first is the binary stage, which employs the binary model, and the second is the truncated stage, which utilises the truncated model. In the initial stage, which is the binary stage, the respondent is presented with the option of subscribing to weather index insurance products or not. Given that the initial stage is the binary decision stage, the probit model was employed. With regard to the second stage, the study employed the zero-truncated negative binomial model to analyse the intensity of subscription. The empirical model for this study is specified as follows:

Binomial model with probit link function:

$$\begin{aligned}\textbf{Subscription}_{\mathbf{i}} = {} & \beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \\ & + \beta_4 Maritalstatus_i + \beta_5 Farmsize_i + \\ & + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ & + \beta_9 Ins.Prompt\ paytm_i + \beta_{10} Ins.Awarnes_i + \\ & + \beta_{11} Weather.info_i + \beta_{12}\ Ext.Serv_i + \\ & + \beta_{13} CreditAcess_i + \beta_{14} RiskEf.Inc_i \end{aligned} \tag{9}$$

Truncated Negative Binomial Model:

$$\begin{aligned}\textbf{Sub.Intensity}_{\mathbf{i}} = {} & \beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \\ & + \beta_4 Maritalstatus_i + \beta_5 Farmsize_i + \\ & + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ & + \beta_9 Ins.Prompt\ paytm_i + \beta_{10} Ins.Awarnes_i + \\ & + \beta_{11} Weather.info_i + \beta_{12}\ Ext.Serv_i + \\ & + \beta_{13} CreditAcess_i + \beta_{14} RiskEf.Inc_i \end{aligned} \tag{10}$$

Study variable

Dependent variable

The nature of the dependent variable was a continues variable. The dependent variable was measured as the ratio of land insured over the total number of land cultivated. Hence, for the purpose of estimation, the dependent variable was converted into a count variable (0,1,2,3,…10), (Kalmijn, 2012). This was done by first multiplying the dependent variable, which is ratio in nature by 10 (for instance 0.25 × 10 =2.5). The second part is to approximate the continues values into the nearest whole number (for instance, 2.5 ~ 3 and 2.2~2). Therefore, the dependent variable is now count variable (number of land insured) and requires the use of count models for its estimation.

Explanatory Variables

Sex of farmer (coded as male 1, female 0), Marital status (coded as married = 1, not married = 0), education (years of education), household size (number of persons in the household), FBO access (Yes = 1 or No = 2), Experience (years), Risk efficient income (T-MOTAD- amount), Weather Information (Yes = 1, No = 0), Insurance awareness (Yes = 1, No = 0), Extension service (Yes = 1, No = 0), Insurance prompt payment = Yes = 1, No = 0), and Credit access (Yes = 1, No = 0).

Results and discussion

Existing plan, optimum plan and risk efficient farm plans on various crops

The major four crop enterprise mix produced in the area became the basis for the farmer's plan and the LP/T-MOTAD selected crop mix. These were maize, sorghum, soya bean and groundnut (GSS, 2016). Table 1 presents the results of the farmer's plan (I), risk efficient farm plans (II and III) and profit maximization plan (IV). The result from Table 1 shows that the farmer's plan (I) is to produce maize (0.54 hectare), soya bean (1.00 hectare), groundnut (0.56 hectare) and sorghum (0.5 hectare) to obtain an expected income of GH¢7,412.97[1] ($673.29). From the Table 1, the result of the profit maximization plan (IV) also shows that to obtain the optimum income of GH¢11168.10 ($1014.36), the farmer should produce 1.50 hectares of soya bean and 0.74 hectare of groundnut. Comparably, the profit maximization plan (IV) gives the farmer about 33.62% increase in income more than the farmer's plan (I). From the Table 1, the risk efficient farm plan (II and III) shows that the farmer should produce soya bean and sorghum in their respective hectares (1.50 ha and 0.33 ha (Plan II) /1.50 ha and 0.42 ha (Plan III) to obtain a risk efficient income of GH¢9,403.42 ($854.08) and GH¢9,835.10 ($893.29) respectively. The risk efficient income obtained by the risk efficient farm plans (II and III) is higher than the farmer's plan by 21.17% and 24.63% respectively. This implies that the farmer can obtain an increased income with less level of risk. However, comparing the risk efficient plans (II and III) and the profit maximization plan (IV), there is a significant decrease in income by 15.80% and 11.94% (risk efficient farm plan II and III) respectively. This significant decrease in the risk efficient farm plans (II and III) is known to be the risk premium for averting a riskier plan.

Subscription of the Weather Index Insurance Product

From the Figure 1, out of 450 food crop farmers interviewed, 287 (64%) noted that they have subscribed to the Weather Index Insurance policy. Approximately 36% (163) of the farmers interviewed also noted that they have not subscribed to the Weather Index. The farmers interviewed asserted that their low income, lack of preferred attributes, and prompt payments, among other factors, is what is constraining them from subscribing to the weather insurance.

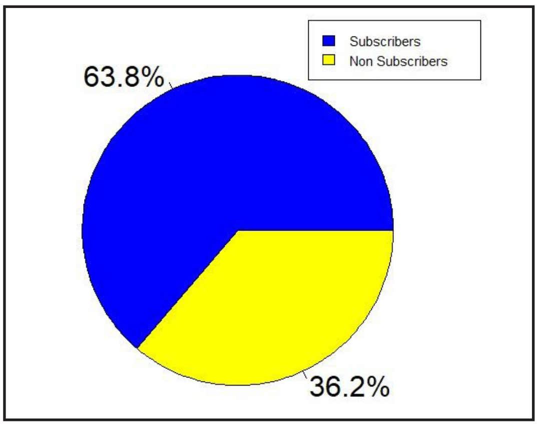
Subscription Intensity of the Weather Index

[1] As of August, 2023, when the data was taken, the exchange rate was approximately GH¢ 11.01 to 1 USD. NB: Current exchange rate is GH¢ 14.33 to 1 USD (Source: https://www.bog.gov.gh/economic-data/exchange-rate/).

	Farmer´s Plan (I)	Risk Efficient Plan (II)	Risk Efficient Plan (III)	Profit Maximization Plan (IV)
Optimal Value (GH¢)	7412..97	9403.42	9835.10	11168.10
Enterprises				
Maize (ha)	0.54	0.00	0.00	0.00
Groundnut (ha)	0.56	0.00.	0.00	0.74
Soyabean (ha)	1.00	1.50	1.50	1.50
Sorghum (ha)	0.50	0.33	0.42	0.00
Total Crop Area	**2.60**	**1.83**	**1.92**	**2.24**

Source: Field survey, (2023)

Table 1: Farmer's Plan, Optimum Plan and Risk Efficient Plan of Crops.



Source: Field survey, (2023)

Figure 1: Distribution of subscribers and non-subscribers of WII in UWR.

Insurance Product

From Table 2, the average land size owned by the farmers is 2.60 ha which is higher than the national average farm size of 2.20 ha for smallholder farmers (MoFA, 2015). The plausible reason is that farmers do not have enough income as well as credit access to expand their farm production activity. Table 2, the average land size insured against these climate extremes using the weather index insurance was 0.65 ha out of the 1.67 ha used for cultivation. Therefore, the subscription intensity of the weather index insurance is 0.39 ha (Area of land insured per land cultivated). By implication it means that for every hectare of farm size cultivated, the farmer insures 0.39 ha. The plausible reason is that most of the farmers interviewed asserted that they are constrained financially, making it difficult to expand their land insured.

Agricultural activity	Mean	Subscription Intensity
Area of land insured using WII (Hectares)	0.65	
Area of land cultivated (Hectares)	1.67	
Area of land owned (Hectares)	2.60	
Subscription Intensity of Weather Index Insurance		0.39

Source: Field survey, (2023)

Table 2: Subscription Intensity of the Weather Index Insurance Product.

Best Fit Model between PRM ZINBM NBDHM using AIC, BIC, LL

In reference to the Table 5 which present the results of the PRM, NBHM and ZINBM in estimating the effect of risk optimum income on subscription and subscription intensity of the WII. The AIC, BIC, and LL from the three count models (PRM, NBHM and ZINBM) employed in the Table 5 have been presented in the Table 3. The results in the Table 3 is to show the performance of all the three count models employed in the study. The results show that NBHM has AIC and BIC values comparatively smaller than that of ZINBM which values are also smaller than that of PRM (i.e. $2557.469<2559.325<10851.4$ for AIC and $2693.074<2694.930<10917.15$ in the case of BIC). As the model with the minimum computed AIC and BIC, NBHM appears to have empirical superiority than ZINBM which is also empirically superior than PRM. Further, the Log-Likelihood results in the Table 3 also portray that NBHM has the biggest log likelihood value of -1246 compared with -1247 for ZINBM and that of PRM which is -5410. This also suggests that NBHM has empirical superiority for the data set than ZINBM and PRM respectively.

Count Models	AIC	BIC	Log-likelihood
PRM	10851.4	10917.15	-5410
ZINBM	2559.325	2694.930	-1247
NBHM	2557.469	2693.074	-1246

Source: Field survey, (2023)

Table 3: Best Fit Model between PRM ZINBM NBDHM using AIC, BIC, Log-likelihood

Vuong test results based on pair comparisons of PRM, NBHM and ZINBM

In the study, PRM was paired as first model with NBHM and ZINBM respectively. Further, the ZINBM was paired as first model with NBHM. The results are presented in the Table 4. The results in Table 4 show that all the computed Vuong test z-statistic values are negative and highly significant. The Vuong test result of -20.2716*** between the Poisson Regression Model (PRM) and the Negative Binomial Hurdle Model (NBHM), implies that NBHM is preferred statistically to PRM. Similarly, test result of -20.2669*** between Poisson Regression Model (PRM) and Zero-Inflated Negative Binomial Model (ZINBM), implies that The ZINBM is statistically preferred to the PRM. Also, between the Negative Binomial Hurdle Model (NBHM) and the Zero Inflated Negative Binomial Model (ZINBM), the Vuong test result of -2.3414*** indicates that NBHM is preferred statistically to ZINBM. Given the study results, Negative Binomial Hurdle Model (NBHM) is selected as the best count model in dealing with excess zeros and over dispersion in the weather index insurance data set.

Count Regression Models	Vuong test z-statistic	p-value
PRM vs NBHM	-20.2716***	2.22e-16
PRM vs ZINBM	-20.2669***	2.22e-16
ZINBM vs NBHM	-2.3414***	0.0026

Source: Field survey, (2023)

Table 4: Vuong test results based on pair comparisons of PRM, NBHM and ZINBM.

Hanging rootogram of the PRM, NBHM and ZINBM for the study's count data

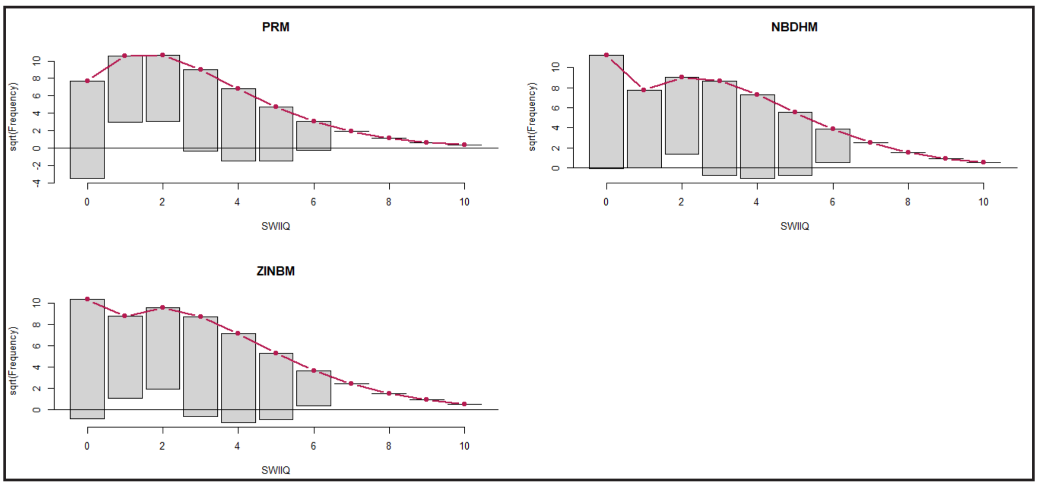
Following the discussions from the Table 3 and the Table 4 in finding the best fit model for the study, that could address the issue of excess zero, under and over dispersion in the WII data set. This study went further to use a hanging rootogram to show which among the three count regression models best fits the study's count data, addresses excess zeros, and treats over and under dispersion in the count data. This is shown in the Figure 2. From Figure 2, Poisson Regression Model (PRM) is at the top-left, Negative Binomial Hurdle Model (NBHM) to the top-right and Zero-inflated Negative Binomial Model (ZINBM) to the bottom left. The rootogram for PRM (top-left) shows that the counts (1, and 2) are over fitted while zero (0) and most count from 3 going are under fitted. This clearly shows over dispersion and a high number of under dispersion in the data. Therefore, a clear lack of fit for zero (0) count means that there is still a possibility of excess zeros in the study's count data.

Also, the rootogram for ZINBM (bottom-left) shows that there is under fitting of zero (0) and counts (3 going) indicating the presence of excess zeros and under dispersion in the count data. Comparably, the Zero-inflated Negative Binomial Model (ZINBM) is a much better fit than the Poisson Regression Model (PRM). However, the rootogram for NBHM (top-right) shows that the model perfectly fits the count zero (0). This clearly indicates that NBHM completely treats the excess zeros. Also, the deviations between the observed frequencies and the predicted frequencies are quiet small for most of the positive counts. Which means that NBHM is the best fit model.

Risk Efficient Income on Subscription and Subscription Intensity of Weather Insurance

In reference to the Table 3 which shows the results of (AIC, BIC, and Log-likelihood), The table 4 which shows the results of the Vuong statistical test and the Figure 2 which presents the results of the rootogram, all results show that the Negative Binomial hurdle model is the best model for this study rather than its competing models (PRM and ZINBM). Therefore, the results of the NBHM on the effect of risk efficient income on subscription and subscription intensity presented in the Table 5 is discussed. From the Table 5, the results of the Negative Binomial Hurdle Model (NBHM) indicate the estimate with their associated standard errors in bracket. In the first regression stage of the NBHM (Zero-hurdle model), the results show that variables such as the age of a farmer, sex, farm size, insurance prompt payment, extension service, credit access and risk efficient income are statistically significant in influencing food crop farmer's decision to subscribe to the weather index insurance. In the second regression stage of the NBHM (Count model), the results show that age, sex, education, farm size, experience, FBO, household size, insurance prompt payment, insurance awareness, credit access, risk efficient income are the variables that are statistically significant in influencing the intensity of farmer's subscription to the weather index insurance.

From the Table 5, the results of zero hurdle and count model of the NBHM show that the age of a farmer has a negative relationship with subscription and subscription intensity



Source: Field survey, (2023)

Figure 2: Hanging rootogram of different count models for the study's count data (0, 1,2,3,4….10).

and is significant at 1% and 10% respectively. This implies that older food crop farmers have extensive knowledge and skills, have dealt with many crop failures and losses, and have gained a lot of experience dealing with risky situations such as climatic or production risk. Therefore, they are more likely not to subscribe to the weather index insurance, let alone increase the number of subscriptions. The results of the zero-hurdle model of the NBHM show that farm size has a negative effect on the subscription for WII insurance and is statistically significant at 5%. This implies, it is more likely that a hectare increase in farm size will reduce the number of people who will subscribe to the weather insurance product. Also, the results of the zero-hurdle model of the NBHM show that access to extension services is found to have a positive effect on the subscription of WII and is statistically significant at 5% level. This implies that increasing extension service access to farmers is more likely to increase the number of farmers who will subscribe to the weather insurance product. This is consistent with a study by Ankrah et al. (2021).

Accordingly, from the Table 5, the results of the count model of NBHM, show that insurance awareness was found to have a negative relationship with subscription intensity of WII and is statistically significant at 1% level. This implies that, it is likely they may be aware of the WII but do not have the purchasing power to increase their subscription intensity. Insurance prompt payment has a positive effect on subscription intensity of the WII and is significant at 10%. This means, it is likely that immediate payment of insurance compensation will attract food crop farmers to increase the proportion of the land size insured. Access to credit was found to have a positive relationship with subscription and subscription intensity, and is statistically significant at 1% and 5%, respectively. This implies that making credit available to the farmers to be able to access is likely to increase the number of farm lands they will insure.

From the Table 5, the results of the zero-hurdle model of NBHM show that risk efficient income has a positive and statistically significant effect on subscription of weather index insurance product. This implies that an increase in the income of the farmer (Risk efficient income) is likely to increase the number of farmers who will subscribe to the insurance product. Interestingly, the count model results of the NBHM shows a negative coefficient for risk efficient income and is statistically significant at 1% level. This means that as the farmer gets a higher income (risk efficient income) than his farm income, it is likely he will no longer be willing to expand the land size insured. The plausible reason is that financial situations are getting better and therefore it serves as enough security to carter for the cost of any unforeseen circumstance.

Variable	Subscription of Weather Index-Based Insurance			Subscription Intensity of Weather Index-Based Insurance		
	PRM	NBHM (Zero Hurdle)	ZINBM (Zero Model)	PRM	NBHM (Count Model)	ZINBM (Count) Model
Intercept	6.9861*** (0.1808)	7.9162*** -1.3987	-12.8891*** (2.4122)	- -	3.9678*** (0.2479)	3.9679*** (0.2479)
Age	-0.0316*** (0.0017)	-0.0467*** (0.0113)	-0.0777*** (0.019)	- -	-0.0046* (0.0027)	-0.0046* (0.0027)
Sex	-0.3563*** (0.023)	-0.6582*** (0.1798)	1.1078*** (0.3093)	- -	-0.0522* (0.0317)	-0.0522* (0.0317)
Education	0.0490*** (0.0116)	-0.0487 (0.0806)	0.0822 (0.1378)	- -	0.0784*** (0.0159)	0.0784*** (0.0159)
Farm Size	-0.0202*** (0.0051)	-0.0938** (0.0406)	0.1478* (0.0672)	- -	0.0220** (0.0068)	0.0220** (0.0068)
Farm Experience	0.0122*** (0.0027)	0.0044 (0.0176)	-0.0087 (0.0294)	- -	0.0118** (0.0039)	0.0118** (0.0039)
FBO	0.0744** (0.0240)	0.0021 (0.1596)	-0.0289 (0.2681)	- -	0.0724* (0.0313)	0.0724* (0.0313)
Household Size	-0.0177*** (0.0043)	-0.0265 (0.0280)	0.0407 (0.0476)	- -	-0.0109* (0.0061)	-0.0109* (0.0061)

Source: Field survey, (2023)

Table 5: Risk Efficient Income and Risk Aversion on Subscription and Subscription Intensity Weather Index-Based Insurance.
(To be continued).

Variable	Subscription of Weather Index-Based Insurance			Subscription Intensity of Weather Index-Based Insurance		
	PRM	NBHM (Zero Hurdle)	ZINBM (Zero Model)	PRM	NBHM (Count Model)	ZINBM (Count) Model
Insurance Prompt	-0.0848*** (0.0215)	0.3191** (0.1485)	0.5356* (0.2493)	- -	0.0565* (0.0279)	0.0565* (0.0279)
Insurance Awareness	-0.1308*** (0.0210)	-0.0726 (0.1443)	0.1105 (0.2397)	- -	-0.1374*** (0.0292)	-0.1374*** (0.0292)
Weather Information	0.1272*** (0.0206)	0.3386** (0.1474)	-0.5164* (0.2473)	- -	-0.0316 (0.0296)	-0.0316 (0.0296)
Extension Service	0.1910*** (0.0211)	0.2925** (0.1442)	-0.5021* (0.2418)	- -	0.0255 (0.0275)	0.0255 (0.0275)
Credit Access	0.3328*** (0.0220)	0.5372*** (0.1560)	-0.8782*** (0.2602)	- -	0.0638* (0.0287)	0.0638* (0.0287)
Risk Efficient Inc.	-0.2872* (0.0178)	0.5209*** (0.1372)	0.8430*** (0.2359)	- -	-0.0602* (0.0246)	-0.0602* (0.0246)
Log (Theta)				- -	4.1618*** (0.2170)	4.1618*** (0.2170)
AIC	10851.4	2557.469	2559.325			
BIC	10917.15	2693.074	2694.93			
Log-likelihood	-5409.7	-1245.735	-1246.662			

Source: Field survey, (2023)

Table 5: Risk Efficient Income and Risk Aversion on Subscription and Subscription Intensity Weather Index-Based Insurance. (Continuation).

Conclusion

Farm income, aside from other factors, remains a key challenge when it comes to the subscription and subscription intensity of the weather index insurance. The paper bridges a literature and methodological gap by looking at risk efficient income obtained using the stochastic risk optimization model (T-MOTAD). The paper also analyses subscription and subscription intensity of weather index insurance. It further analyses the influence of the risk efficient income, prompt payout, insurance awareness, weather information, credit access and extension service among factors on subscription and subscription intensity using the negative binomial hurdle model. Furthermore, the study empirically tested the Negative Binomial Hurdle Model and two other count models (Poisson Regression Model and Zero-inflated Negative Binomial Model) using the AIC, BIC, Log-likelihood ratio test and Vuong statistical test to determine which among them is the best fit model for the study. The result from the T-MOTAD shows that the risk optimum plan was for the farmer to produce soya beans and sorghum to obtain a risk efficient income. The results from subscription and intensity also show that about 64% of the farmers have subscribed to the weather index insurance. Therefore, the proportion of the farm insured per land cultivated by the subscribers was 0.39 ha. The results from the negative binomial hurdle model shows that factors such as risk efficient income, insurance prompt payout, credit access, extension service, education, age, farm size and experience are statistically significant in influencing food crop farmer's subscription and subscription intensity of the weather index insurance.

The study contributes to the literature by adding to the limited number of studies on subscription, and subscription intensity. This study is unique as it integrates a risk-efficient farm plan with subscription of the weather index insurance product as a support policy, marking it the first initiative of its kind within the Ghana empirical context. The study also bridged the methodological gap by testing the empirical superiority of the negative binomial hurdle model and the zero-inflated negative binomial model as advancements over the Poisson regression model in analyzing the study's count data. This will benefit the research community in that it will provide a reference literature for further work relating to subscription and subscription intensity as well as risk optimum farm plan. This study suggests collaboration between government agencies, insurers, and extension officers to educate farmers about weather index insurance. Prompt payouts and focusing on crops identified by the T-MOTAD model could incentivize participation. Further research is needed on how risk-reducing farm plans affect farmers' willingness to pay for this insurance.

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