



Characterizing Risk Behaviour of Maize Farmers using the Experimental Gambling Approach: An Empirical Study in Ghana

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Abstract

Along the maize value chain in Ghana are a wide range of risks that confront actors; the risk chain actors' face include production and marketing risks. Accordingly, risk management, which has become an integral part of maize value chain activities, is challenged with several factors, some of which are economic, institutional, social and behavioral factors. This study posits that risk preferences/behavior of farm decision-makers in the maize value chain have empirical importance for economic and policy analysis. Thus, an experimental gambling approach was used to elicit the risk aversion behavior of respondents (farmers). Here, the respondents' risk aversion behavior over varying game levels was investigated. The multinomial logit model was used to investigate endogenous and exogenous factors explaining the risk behavior. The data were obtained by interviewing 220 maize farmers who were sampled with a two-stage sampling procedure. This study revealed that most of the farmers in the study area exhibited risk aversion behavior. About 33% of farmers showed extreme risk aversion behavior at the games' lowest level and increased to 45% as the game level rose. It was also found that sex, age, level of formal education, access to credit, access to the storage facility, household size, farm size and the number of extension visits to the farm significantly explained the risk aversion behavior the maize farmers exhibited. Because farmers are risk-averse and become more risk-averse as stakes become high, any farm innovations to be introduced to them must be implemented gradually, especially with the low-income farmers. It is also critical to make risk mitigation 'handles' available to farmers so that they can rely on them during times of risk.

Keywords: agricultural decision making; experimental gambling; farmer preferences; Ghana; maize farmers; risk attitude

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INTRODUCTION

Small-scale rural farmers dominate Ghana's agricultural industry, which contributes significantly to the country's economy (Ghartey et al., 2014). In 2019, this industry employed over 33.5% of the country's workforce and contributed 19.7% to the gross domestic product (GDP). The sector is the country's second-

largest employer. However, it is the smallest in contrast to services and industry (Embassy of Israel, 2020). Agricultural economists and other development specialists generally agree that investing in agriculture is an effective strategy for reducing poverty, inequality and hunger, especially in countries where the sector employs a large share of the population (FAO, 2012). Furthermore, the agricultural sector,

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as is well known, is vulnerable to natural disasters and has historically been a more risky endeavor, particularly in low-income countries like Ghana, compared to the non-agricultural sectors (Embassy of Israel, 2020). Agriculture is such a crucial element of a low-income country's total economy that hazards influence not only rural people's lives but the entire economy, including non-agricultural sectors (Zeweld et al., 2019). As noted in the agriculture sector review in Ghana by the Embassy of Israel (2020), poor farmer adoption of technology is one of the biggest challenges facing Ghana's overall agricultural production. They further suggested that farmers are typically reluctant to accept new technology because they are unfamiliar with it or are unsure how it will improve their yield, promote food security and ensure sustainable agricultural production. In short, one could say that risk aversion behavior is one of the factors that directly affects maize farmers' ability to adopt sustainable agricultural production systems and the strategies to handle various types of risks (Sulewski and Kłoczko-Gajewska, 2014). Risk aversion is a primary driver of farm-household decision-making and has a significant impact on smallholder farmers' adoption of these innovative systems (Yu, 2014). People's risk preferences are described as their willingness to take risks. Kouame and Komenan (2012) also asserted that farm households in developing countries are known for being slow to adopt new agricultural technologies even though prospective to provide higher returns on land and labour than the current methods. Their fear of taking chances is one element leading to their anxiety (Kouamé, 2010). Surprisingly, multiple studies have discovered that a farmer's risk attitude has a significant impact on the possibility of applying any risk management strategy, even if the risk management technique is proven to be unaffected by the farmer's risk perceptions (Van Winsen, 2014).

Risk management adjustments are influenced by the types of dangers encountered and attitudes toward those risks. Therefore, knowing how farmers feel about risk can help them deal with and adapt to agricultural shocks and risks, particularly crop production. Because judgments made in the face of uncertainty are subject to systematic variation and social factors, resource distribution and availability, as well as other distinctive aspects such as

human experience, risk attitude is neither exogenous nor fixed (Zeweld et al., 2019). As a result, farm households' selection of various risk management strategies has been very challenging and varies widely between individuals and thus, risk preferences must be examined and measured to undertake economic analysis and make policy recommendations, especially in developing countries (Monjardino et al., 2021). Hence, understanding farmers' risk preferences can help with farm management and rural development projects, technology development and transfer and policy building to promote sustainable agricultural production (Kouame and Komenan, 2012). Due to the intricacy of structural models of farm management under uncertainty and the noisy nature of observational data, it is difficult to define exactly how risk and risk preferences influence field behavior (Hellerstein et al., 2013). There is a growing consensus in the agricultural economics literature that farm operators' risk-taking preferences are crucial in uncertain conditions. As a result, it is empirically important to conduct periodic research to assess farmer risk attitudes to update policy formulations (Yesuf and Bluffstone, 2018). In agriculture, sustainable practices are hard to maintain due to numerous risks that confront farmers. It is evident that the growing instability confronting agricultural households, including volatility in yields, prices and agricultural income, poses a long-term threat to the sustainability of the entire agricultural sector and food supply (Meuwissen et al., 2018; Iyer et al., 2020). Accordingly, farmers' risk behavior, which is a function of their perceptions of the future state of events, can influence their ability to implement sustainable farm practices (Nastis et al., 2019; Iyer et al., 2020). Therefore, to better understand farmers' decision-making for sustainable production amidst high risk in agriculture, it is necessary to address farmers' risk behavior. The current study contributes to the agenda to ensure a sustainable agricultural system by providing empirical evidence of farmers' risk behavior to pave way for policy recommendations that will positively influence farmers' decision-making to implement sustainable practices.

The methods of assessing risk aversion are the econometric approach, the comparison of programming model outcomes with real farms and the direct elicitation of risk aversion. All of

these methods have drawbacks, most importantly in developing countries. The availability of relevant data frequently limits the applicability of econometric models. The programming model often assumes models that can perfectly predict farmers' reactions. The direct elicitation of risk aversion is estimated by asking farmers to choose between hypothetical options with varying risk exposure. However, individuals are not rationally consistent in their responses and in hypothetical situations, their responses are often biased (Kouame and Komenan, 2012). Direct in-person elicitation yields the most precise, individual-specific results. Experimental approaches ensure that the elicited risk measure is impacted only by risk preferences and not, for example, by variable estimates of the outcome distribution. One of the experimental approaches is Binswanger's innovation in India, which allows an individual to gamble under-regulated risk settings with high payoffs, a risk that can be equated to investment decisions in normal situations. This method overcomes the majority of procedures' flaws and allows for direct risk aversion elicitation (Kouamé, 2010). The key disadvantage is the high expenses, which provide sufficiently large payoffs to guarantee players' commitment. This disadvantage does not pose an issue in developing countries, as it would in rich countries (Kouame and Komenan, 2012).

In Ghana, most studies on risk attitude measures have not looked at the experimental gambling approach. Our paper, therefore, seeks to report the risk aversion behavior of maize farmers using this approach. We also identified the factors that explained the risk aversion behavior of maize farmers. This paper proceeds as follows: looking at the methodology to obtain the data and explaining sampling process and data collecting procedure, followed by the experimental gambling and concluded with the presentation of the econometric modeling to estimate determinants of risk aversion behaviors. This paper subsequently presents the results of data analysis and in-depth discussion. The final section of the paper presents conclusions and recommendations.

MATERIALS AND METHOD

The survey

The study population included all maize producing farmers in Nkoranza South and

North Districts in the Brong-Ahafo Region of Ghana, with 223 and 267 registered maize farmers, respectively. This study employed a two-stage sampling procedure to select respondents. In the first stage, the districts were purposively selected, each of which was divided into three maize farming zones based on the geographical or ecological locations of farms (forest, grassland and guinea savannah), with a total of six (6) farming zones. Next, the proportional random sampling technique was employed to select 220 maize farmers to take part in the survey. The decision to sample 220 maize farmers for the survey was arrived at after using the Yamane formula (Tepping, 1968; Inkoom et al., 2020) to determine what appropriate sample size ought to be. The formula applied is as shown in Equation 1. The data was then collected from the selected farmers from May 11 to 31, 2019.

$$n = \frac{N}{1 + Ne^2} \quad (1)$$

where; n = sample size; N = population size = 480; e = level of precision = 0.05

Elicitation of risk aversion behaviour: The experimental gambling procedure

In assessing the risk aversion behavior of maize farmers, the experimental design developed by Binswanger (1980) was adopted and modified. The Binswanger design has become a conventional multiple price list experiment commonly used to elicit risk aversion behavior in the classical literature see for example Kouamé (2010); Dadzie and Acquah (2012); Aidoo et al. (2014); Domingo et al. (2015). In the experiment, the respondents were confronted with a series of choices among sets of alternative prospects (gambles) involving real money payment. The average daily wage (popularly known as "by day") of the area was Gh¢25.00 (about 6.00 USD). The amounts listed provide a significant incentive for the respondents to carefully consider the options and reveal their true risk preferences. The respondents' choices among alternative prospects were indications of the degree of risk aversion (Kouamé, 2010). All of the three gambles were used in the experiment. Each gamble had six prospects, including O, A, B, C, D and E, each of which with 50%

winning probability. The safe alternative is the O. In every gamble, a respondent had an opportunity to select a prospect, and afterwards, a coin was tossed. The respondent received the left-hand amount if the coin showed head or right-hand amount if the coin showed tails as shown in Table 1 (i.e., the first three columns in the table).

To observe the risk attitudes of farmers following different outcomes and hence the nature of partial risk aversion, experiments were conducted at different levels. Each respondent had the opportunity to play games 1, 2 and 3 respectively. Games 2 and 3 were derived from game 1 (GH¢20 game), by multiplying all amounts in game 1 by 2.5 and 5 respectively,

as scale-up factors to raise the stake levels. The first game (game 1) was real, meaning that the individual received the payment based on the outcome of the experimental gamble. But due to budget constraints, game 2 and game 3 were treated hypothetically. Before the respondents played the games, they were informed that they would receive payment for one of the games based on the outcomes. In this way, the respondents played all games as real games. After a respondent had finished playing a game, he/she was paid duly based on the outcome of game 1. After that, how risk aversion coefficients serve as a measure of the level of risk aversion from the farmers' responses for completing the experimental games was explained.

Table 1. The basic structure of the risk aversion experiment

Choices	Bad outcome "Heads"	Good outcome "Tails"	Expected gain	Standard deviation or spread	CPRA coefficient (S)	Risk classification
O	20	20	20	0	∞ to 7.47	Extreme
A	18	36	27	9	7.47 to 2.00	Severe
B	16	48	32	16	2.00 to 0.85	Intermediate
C	12	60	36	24	0.85 to 0.32	Moderate
D	4	76	40	36	0.32 to 0	Slight to neutral
E	0	80	40	40	0 to $-\infty$	Neutral to preferring

Note: CPRA = constant partial risk aversion; 1USD = GH¢4.40 at the time of the survey

Source: Adopted and modified from Binswanger (1980)

Data processing and analytical methods

Estimation of risk parameter

The parameter assumes that individuals maximize their expected utility (EU) given the risk parameter in the scenario, the constant partial risk aversion (CPRA) utility function while estimating risk preference. The CPRA parameter describes a person's risk aversion and completely explains the utility function's curvature. The formal presentation of the CPRA utility function employed is given as follows (i.e. Equation 2).

$$U = (1-S)c^{(1-S)} \quad (2)$$

Where; S defines the CPRA coefficient and c is the certainty equivalent of a prospect. If a respondent is indifferent between two consecutive prospects (say 1 and 2) given that both prospects have equal probabilities of a good or bad outcome, then we have $1, 2$ $E(U_1) = E(U_2)$ and hence $(1-S)c_1^{(1-S)} = (1-S)c_2^{(1-S)}$.

Thus, the partial risk aversion coefficient S is computed by solving the equation for the indifference (equal expected utility) between two consecutive alternatives, using the CPRA utility function. The upper and lower limits of the CPRA coefficients for each prospect of the experiment are given in Table 1. The intervals were determined by calculating the value of S that would make the individual indifferent between the prospects they chose and the two adjacent prospects (Mohan, 2020). For example, in this study, a choice of Lottery 3 implies a risk coefficient in the interval of (2, 0.85): indifference between Gambles 2 and 3 corresponds to $S = 2.0$ and indifference between 3 and 4 to $S = 0.85$.

Model estimation

Farmers may adopt innovations to maximize utility, such as profit and risk (Kabunga et al., 2012) when the expected utility from adopting the innovation is higher than the current innovations. In other words, a farmer compares the expected utility from those adopting

technology and from those not adopting and decides to adopt it if the net expected utility exceeds zero otherwise not (Van Winsen, 2014). Accordingly, the expected utility function that shows the farmer's choices between risky or uncertain prospects is given mathematically by Equation 3.

$$U(.) = \text{Max}U(\text{II}) \quad (3)$$

Where; the expected utility $U(.)$ depends on a vector of constraints (II), such as resources, wealth and farmer-specific characteristics. Its shape varies (convex or concave), because an individual may be risk-loving for some prospects while being risk-averse for others (Zeweld et al., 2019). The expected utility is unknown, but the farmers' risk-taking behavior can be observed. The unobserved factors can be inferred from the observed factors, which is quite noteworthy (Teklewold et al., 2017). Our experimental data have a feature that is categorical in nature, for instance, extreme and severe risk aversion columns classified as high-risk averse categories (Kouamé, 2010). With such categorical data, the multinomial probit model is most appropriate. This method has the advantage of not requiring us to assume a certain form of the utility function; instead, we represent farmer risk attitudes using the underlying latent variable. The normal equation for the farmers' choice towards risks is given by Equation 4.

$$RA_{ij}^* = B_i X_i + e_{ij} \quad (4)$$

Where; RA is an observed response variable for farmers' risk attitudes while RA^* is a latent variable of risk attitudes, which depends on a vector of explanatory variables (X_i) and a random error term (e_i). The error term measures farmers' random taste shocks (i.e., changes in a farmer's preference for their choice towards risks, j), which are not visible to

the researchers but still known to the farmers (Westover, 2019).

$$RA_i = \begin{cases} j, & \text{if } RA_j^* = \max(RA_{i1}^*, RA_{i2}^*, \dots, RA_{iM}^*) \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

$$P(RA_i=j) = \frac{\exp x_{ij}^j \beta}{\sum_{i=1}^M \exp x_{ij}^i \beta} \quad (6)$$

Following the Equation 5 and 6, when estimating the multinomial model for the dependent variable with j categories, the estimation would be $j-1$ linear equation (Tran and Goto, 2019). In this current study, there were three (3) j categories so two equations were estimated as shown in Equations 7 and 8. Where $P(RA_i = 2)$ defines the probability of a farmer choosing a high-risk aversion category and $P(RA_i = 1)$ defines the probability of a farmer choosing the moderate-risk aversion category. The reference category is denoted as $P(RA_i = 0)$, that is, the probability of an individual being in the low-risk aversion category.

$$\ln \left(\frac{P(RA_i=2|X)}{p(RA_i=0|X)} \right) = \beta_{02} + B_{2k} X_{ik} = RA_{2i} \quad (7)$$

$$\ln \left(\frac{P(RA_i=1|X)}{p(RA_i=0|X)} \right) = \beta_{01} + B_{1k} X_{ik} = RA_{1i} \quad (8)$$

The linear expression $\beta_{02} + B_{2k} X_{ik}$ explains more precisely the probability of a farmer being high risk-averse relative to the probability of the farmer being a low risk-averse. Similarly, the expression $\beta_{01} + B_{1k} X_{ik}$ also explains the probability of a farmer is in a risk-averse category relative to the probability of being in a low-risk category. Following that $i = 1, 2, 3, \dots, 220$ and $k = 1, 2, \dots, 8$, the equations are further expanded to capture farmers' socio-economic characteristics in the empirical estimation as in Equations 9, 10 and 11.

$$RA_{ji} = f(\text{Se, Age, Edu, Hhs, Ext, Acc, Stg, Fms}) \quad (9)$$

$$\ln \left(\frac{P(RA_i=2|X)}{p(RA_i=0|X)} \right) = \beta_{02} + \beta_1 \text{Se}_i + \beta_2 \text{Age}_i + \beta_3 \text{Edu}_i + \beta_4 \text{Hhs}_i + \beta_5 \text{Ext}_i + \beta_6 \text{Acc}_i + \beta_7 \text{Stg}_i + \beta_8 \text{Fms}_i = RA_{2i} \quad (10)$$

$$\ln \left(\frac{P(Y_i=1|X)}{p(Y_i=0|X)} \right) = \beta_{01} + \beta_1 \text{Se}_i + \beta_2 \text{Age}_i + \beta_3 \text{Edu}_i + \beta_4 \text{Hhs}_i + \beta_5 \text{Ext}_i + \beta_6 \text{Acc}_i + \beta_7 \text{Stg}_i + \beta_8 \text{Fms}_i = RA_{1i} \quad (11)$$

Table 2. Definition and measurement of variables

Variable	Definition	Measurement	A priori expectation
Explanatory variables			
Se	Sex of farmer	Male = 1, female = 0	+/-
Age	Age of farmer	Years	+/-
Edu	Level of formal education	Years	+/-
Hhs	Household size	Number	+/-
Ext.	Number of extensions visit to a farm	Number	+/-
Acc	Access to credit	Yes = 1, No = 0	+/-
Stg.	Access to the storage facility	Yes = 1, No = 0	+/-
Fms	Farm size	Hectares	+/-
Dependent variable			
Risk	High risk-averse	High risk-averse = 1, other = 0	N/A
aversion	Medium risk-averse	Medium risk-averse = 1, other = 0	N/A
	Low risk-averse	Low risk-averse = 1, other = 0	N/A

RESULTS AND DISCUSSION

Descriptive analysis

Table 3 presents the descriptive statistics of the farmers. All the 220 farmers responded to questions on their socio-economic characteristics. The results showed that 145 (66%) of the farmers were males and 75 (34.1%) were females. This might be because males normally have greater access to farmland and are physically stronger than females in maize production. Most of the farmers (58.2%) were also reported

to have access to credit from both the formal and informal sectors. Furthermore, less than half of the farmers (45%) were found to have access to the storage facility. This suggests that price risk management among maize farmers is low since storage is used to manage price risk. The survey revealed that the average age of the farmers was 49 years old. This signifies that most of the maize farmers are commonly older people because maize farming is less attractive and lucrative to young people (Freeman and Mungai, 2018).

Table 3. Descriptive statistics of variables

Categorical variable	Frequency	Percentage	Minimum	Maximum
Sex:				
Male	145	65.90	-	-
Female	75	34.10	-	-
Access to credit	128	58.20	0	1
Access to storage	98	44.60	0	1
Continuous variable				
	Mean	Std. Dev.	Minimum	Maximum
Age	48.84	11.74	25	72
Education	10.49	2.78	0	16
Household size	5.36	1.91	1	10
Farm size (hectares)	4.18	2.60	0.8	15
No. of extension visit	4.85	1.61	0	10

The mean length of formal education of maize farmers was 11 years, the basic school education level that was consistent with the work of a previous study (Aidoo et al., 2014). Households were moderately large with an average size of about 5 individuals. This is a typical farming community where family labor is very important (Tasila Konja et al., 2019). Large family size

implies farmers become more risk-averse since the dependency ratio increases because parenthood increases. The average farm size was about 4.2 hectares. Farmers were found to have access to extension services with mean farm visits of five (5) within a production year of farming. The work of Tasila Konja et al. (2019) also concluded that many farmers have access

to extension services. Since extension services provide farmers with knowledge on the production and marketing of their produce, farmers are likely to have increased access to advisory services on farming practices and marketing of their produce during the farming season (Bashiru et al., 2014; Danso-Abbeam et al., 2017). Farmers with access to extension services can learn about new agricultural technologies important for enhancing the yield of staple food crops (Tasila Konja et al., 2019).

Risk aversion behavior of maize farmers

The results presented in Table 4 indicate that the farmers responding to the experimental gambles exhibited higher risk aversion behavior in game 1 (Gh¢20), game 2 (Gh¢50) and game 3 (Gh¢100), reaching 51%, 60% and 67%, respectively.

This implies that as the gambling stake changes, some farmers exhibit changing risk aversion behavior such that they tend to become more risk-averse in gambles involving higher

stakes. To buttress the point being made, it can be noted that about 13% more farmers exhibited a behavior change to become severe to extreme risk-averse from lowest game level 1 to highest game level 3. That is, at the lowest game level, about 33% of the farm households chose the alternatives representing severe to extreme risk aversion. This proportion increases to about 45% at the highest level of the game. However, the results are in contrast with slight risk aversion, neutrality and risk preferring from the lowest game level to the highest game level, where the proportion declined from 28.1% in game 1 to 21.8% in game 3. The share of responses falling into the intermediate and moderate risk aversion categories remained stable between games 1 and 2 (39.5% and 39.1%) but declined to 33.3% in game 3 due to increases in the severe and extreme risk aversion categories. These results signpost increasing partial risk aversion in which individual farmers are more risk-averse as the size of the game increases. This leads to two possibilities.

Table 4. Distribution of risk aversion behavior of farmers by game level

Category	Game level 1 Gh¢20 (%)	Game level 2 Gh¢50 (%)	Game level 3 Gh¢100 (%)
Extreme	9.1	7.7	18.6
Severe	23.2	29.5	26.4
Intermediate	18.6	22.7	21.4
Moderate	20.9	16.4	11.8
Slight-to-neutral	18.6	17.7	15.9
Neutral-to-preferring	9.5	5.9	5.9

Farmers have low income or smaller “income basket” and therefore, their fear of loss contributes to their risk aversion (Albert and Duffy, 2012; Akhtar et al., 2018) and avoidance of uncertain situations (Akhtar et al., 2018). The fear of losing grows as the size of the stake increases, relating to their level of income or wealth, making them more risk-averse. When there is a possibility of loss, risk aversion rises (Yesuf and Bluffstone, 2018). This practically implies that, even if overall general poverty levels among farmers are considered, any agricultural-based efforts created for farmers must be meticulously designed and implemented at a much slower pace with extremely low-income farmers than with higher-income farmers (Agboola et al., 2018). The other side of the coin is that farmers’ risk aversion may have been impacted by possible earlier losses

in games at levels 1 and 2. As widely known, success can build on success even in poorer areas, so people are more willing to accept risks if things have gone well in the past. Therefore, any farmer who has lost in prior rounds may choose to avoid losing again (Yesuf and Bluffstone, 2018). Farmers’ risk aversion is associated not only with lower wages but also with previous shock experiences and other riskier agricultural techniques that may have resulted in poor harvests and thus a lower return to labor (Adnan et al., 2020). Because risk mitigation options are limited or absent, reactions to risk or risk aversion greatly affect the decisions, such that farmers would be more likely to adopt less hazardous initiatives with adequate rewards as a result of previous failures (Agboola et al., 2018). Therefore, a farmer who is more risk-averse will be more

willing to invest in risk management insurance and risk-reducing farming practices (Hellerstein et al., 2013).

There have been similar games played by peasant farmers in other areas since the first field experiments with Indian farmers by Binswanger (1980). The result appears consistent with the work of Yesuf and Bluffstone (2018), conducted in Ethiopia. However, it is in contrast with that of Kouamé (2010) and Kouame and Komenan (2012) conducted in Côte d'Ivoire. The proportion of farmers falling in the extreme to severe risk category is higher as in the Ethiopian experiment, but it is low in the Côte d'Ivoire's. The higher level of respondents who are high risk-averse suggests that the Ghanaian farmers are more risk-averse. The findings are also consistent with the identification in the previous study by Dadzie and Acquah (2012) that Ghanaian farmers are risk-averse.

The risk aversion behavior of farmers is an important factor in shaping their adoption decisions (Yu, 2014) and therefore, the risk attitudes explain how they act on perceived opportunities and challenges (Domingo et al., 2015). These farmers are more risk-averse and this would largely affect their adoption decision and the direction of the impact of risk attitudes on adoption is empirical (Agboola et al., 2018). More risk-averse farmers may be more inclined to use a risk management tool to manage their risk exposures (Franken et al., 2012) to avoid risk. They are more willing to adopt innovations than their low risk-averse counterparts. Similarly, such farmers may later adopt innovations (Liu, 2013).

Factors explaining risk aversion behavior of maize farmers

The results of the multinomial logistic regression model are given in Tables 5, 6 and 7. The dependent variables measure the degree of farmers' risk aversion behavior. Accordingly, the dependent variables as captured in the estimated models are categorized into high risk-averse, medium (moderately) risk-averse and low risk-averse (Table 2). Here, the "low-risk-averse" was selected as the reference category in the estimation process. The results of this study revealed an inverse relationship between sex and risk aversion behavior of farmers for all the game levels in the experiments and interestingly,

the relationship was significant with high risk-averse as the game level rose from Gh¢50 game to Gh¢100 at 5% significance level. The result is a confirmation that generally female farmers are more risk-averse than male farmers consistent with the work of Yesuf and Bluffstone (2018). Females show high risk aversion behavior when the risk at stake or risk associated with a choice or prospect is high and this is supported by the fact that females tend to reduce their risk assets when the number of children increases. It also suggests that males are more risk-takers (loving) than females (Gebre et al., 2019). Females are more likely to be occupied at home, whilst males are more likely to be active in dangerous outdoor activities. In comparison to males, females do not have as much experience coping with risk (Eckel and Grossman, 2008). They are more susceptible to cultural conventional expositions or limitations, making them less willing to take risks (Gebre et al., 2019). It is also an indication of an early decision of innovation adoption among males, compared to women. Experts view that risk-loving farmers are innovators or early adopters and more interested in learning new things (Albert and Duffy, 2012; Riverola et al., 2016).

Farm size was also found to be inversely related to the farmers' risk aversion behavior. The revealed empirical relationship was significant with high risk aversion as the game level rose from Gh¢50 game to Gh¢100. Farm size (land size) is normally used as a proxy for wealth measure mostly in rural farming communities (Zeweld et al., 2019). Moreover, wealthier farmers are more willing to take risks than their other counterparts (Yesuf and Bluffstone, 2018), which suggests that farmers with smaller farm sizes are more risk-averse. Larger landholders, according to Saqib et al. (2016) are risk-takers more than small landholders. According to Fernandez-Cornejo et al. (2007), adoption of innovations occurs faster on larger farms than on smaller farms. As is widely known, the uncertainties associated with innovations, transaction and information costs are typically higher, limiting participation by smaller farm holders. As a result, smaller farms have lower income levels and taking risks that would further reduce income levels is not permissible (Fernandez-Cornejo et al., 2007).

Table 5. Multinomial logistic regression at Ghç20 game level

Variables	High risk-averse		Moderately risk-averse	
	Estimates	Std. error	Estimates	Std. error
Sex	-0.84	0.542	-0.736*	0.477
Age	0.102**	0.031	0.053*	0.028
Household size	0.058	0.161	0.016*	0.157
Formal education	-0.071	0.045	-0.039*	0.042
Access to credit	0.700	0.452	0.290	0.405
Farm size	-0.164	0.112	-0.061	0.094
Access to storage facility	0.269	0.479	0.204	0.432
No. of extension visit	-0.126	0.146	0.174	0.128
Intercept	-3.359	8.054	-2.273**	1.051
Model summary				
-2loglikelihood	Cox and snell R square		Nagelkerke R square	
351.756	0.119		0.135	
			Chi-square	
			22.29	

Table 6. Multinomial logistic regression at Ghç50 game level

Variables	High risk-averse		Moderately risk-averse	
	Estimates	Std. error	Estimates	Std. error
Sex	-0.730**	0.302	-0.317	0.303
Age	0.057***	0.170	0.026	0.170
Household size	0.065	0.100	0.163	0.102
Formal education	-0.045	0.047	0.018	0.048
Access to credit	0.410	0.262	0.115	0.261
Farm size	-0.129*	0.061	-0.080	0.058
Access to storage facility	0.264	0.275	-0.101	0.275
No. of extension visit	0.057	0.084	0.241**	0.082
Intercept	-1.854**	0.702	-2.600***	0.731
Model summary				
-2loglikelihood	Cox and snell R square		Nagelkerke R square	
340.948	0.219		0.247	
			Chi-square	
			43.588***	

Table 7. Multinomial logistic regression at Ghç100 game level

Variables	High risk-averse		Moderately risk-averse	
	Estimates	Std. error	Estimates	Std. error
Sex	-1.115**	0.546	-0.371	0.541
Age	0.072**	0.029	0.015	0.029
Household size	-0.004	0.158	0.085	0.166
Formal education	0.009	0.048	-0.018	0.050
Access to credit	-0.034	0.450	-0.371	0.442
Farm size	-0.229**	0.107	-0.148	0.101
Access to storage facility	0.825*	0.478	0.044	0.470
No. of extension visit	0.118	0.147	0.512***	0.153
Intercept	-2.389**	1.137	-1.879*	1.141
Model summary				
-2loglikelihood	Cox and snell R square		Nagelkerke R square	
336.372	0.220		0.249	
			Chi-square	
			43.712***	

Note: *** = significance 1%; ** = significance 5%; and * = significance 10%. (Outcome risk aversion category = Low risk aversion is the comparison group)

Farmer's age, on the other hand, had interestingly a significant positive relationship with high risk aversion of farmer's behavior. The result is similar to that of the works of Altobelli et al. (2021), Dilshad et al. (2019), Iqbal et al. (2016) and Ullah et al. (2015) and in contrast with the works of Dadzie and Acquah (2012) and Saqib et al. (2016). The positive and significant coefficients of age show that aged farmers are more risk-averse than young farmers and thus when the age increases, farmers become more risk-averse. Older farmers tend to be more conservative, preventing them from venturing into riskier tasks (Ferede et al., 2017). Also, they are more sensitive to risks and less likely to invest reluctant to take a risk that might affect their income levels, especially for long time investments (Leavy and Smith, 2010). From the results, it can be deduced that younger farmers are low risk-averse, making them more risk-takers.

A significant positive relationship was found between access to the storage facility and high risk aversion behavior at the highest game level. Risk-averse farmers tend to store more quantities of maize to avert price risk. Storage provides them the opportunity to spread their sales at different times during the storage season and helps farmers to take advantage of different market season prices using temporary arbitrage (Gilbert et al., 2017). Farmers are more risk-averse when they have increased access to storage, which makes them reluctant to adopt innovations that will reduce income levels, especially those intended to manage price fluctuations (Mofokeng, 2012; Anastassiadis et al., 2014). However, Owach et al. (2017) discovered that risk-neutral farmers preferred to store more grains. In other words, storage incurs cost and time, so if the costs/risk associated with innovations, particularly those that require prior storage, are high, it will have a negative impact on farmer income levels and the farmer will not adopt such innovations (Kotu et al., 2019).

Finally, this study found a positive relationship between the number of extension visits to a farm in a particular farming season and the risk aversion behavior of farmers as the game progressed from the Gh₵50 game to the Gh₵100 game. The relation was significant with moderately risk aversion behavior of farmers from Gh₵50 game to Gh₵100 game level. Hall (2013) also found a significant positive relationship

between producer interest in additional education training and risk aversion behavior. Participation in extension is a farmer's most important source of knowledge on innovation adoption. As a result, a farmer's increasing participation in extension services is likely to encourage the use of agricultural technology, which will help to ensure long-term agricultural production (Kassem et al., 2021). The extension services educate farmers on new agricultural technologies and innovations that will improve their maize production and marketing activities rather than make them worse. In that case, increasing the number of extension services available to farmers will enable them to take moderate risks that will increase or maintain their income level (Bashiru et al., 2014). Therefore, a farmer's access to extension services is likely to make him or her risk-averse.

CONCLUSIONS

This study concludes that most farmers exhibit risk aversion behavior as the stakes increase. Risk aversion is a general phenomenon as depicted by the significant inverse intercepts in the regression analyses. Farm innovations introduced must be implemented gradually, especially to low-income farmers. Sex, farm size, age, farm storage capacity and the number of extension service visit significantly explain the risk aversion behavior of maize farmers. We recommend that farmers should go into cooperatives to promote easy adoption of innovation. We suggest studies concerned with predicting factors that explain farmers' risk aversion behavior towards patronizing innovations to be conducted before developing the innovations.

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