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Risk, ambiguity and willingness to participate in crop insurance programs: Evidence from a field experiment*

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This paper analyses smallholder farmers' willingness to participate in crop insurance programs, using recent data from cocoa farmers in Ghana. Given the significance of output uncertainty and imperfect capital and insurance markets, we develop a theoretical framework to analyse how risk and ambiguity aversion, and liquidity constraints influence farmers' crop insurance participation decisions. We employ field experiments to elicit farmers' ambiguity and risk aversion, the stated preference approach to obtain information on farmers' willingness to participate in crop insurance programs, and a discrete choice model to examine the factors that influence their participation decisions. We find that risk preferences, ambiguity aversion, and liquidity constraints influence farmers' willingness to participate in crop insurance programs. The results also reveal that the probability of participating in crop insurance programs is positively influenced by wealth, trust and education of the farmers.

Key words: ambiguity aversion, crop insurance, field experiments, liquidity constraints, risk aversion.

1. Introduction

The life of the poor is often inundated with exposure to significant risks and uncertainties: rains fail, livestock die, input and output prices fluctuate. The consequences of such exposure are often dire when the poor have less access to efficient and effective mitigation measures. The economics and behavioural literature, for example, recognise the tendency for the poor to be perpetually trapped in poverty because of poor decision-making under risky and uncertain conditions (Barnett et al., 2008; Mani et al., 2013). Barnett et al., (2008), in particular, point out that to reduce their exposure to risks and

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uncertainties, the poor reduce their investments in high-risk, high-returns ventures, thereby failing to accumulate wealth to spur them out of poverty. After shocks occur, the poor may undertake desperate measures, including the sale of their productive assets, which is often inadequate to generate the needed incomes to help them out of their misery. Under extreme conditions, they may drastically cut down on food expenses, reduce expenditures on health, and even withdraw children from schools, leading to potentially long-term adverse consequences. Owing to these, measures to mitigate the poor's exposure to risks and uncertainties loom large in the development policy agenda (Gazali & Abdulai, 2020).

Indeed, existing evidence support claims that when the poor take up agricultural insurance, by transferring income between states of nature, they tend to benefit. For example, when farmers purchase insurance, they tend to increase investments in inputs such as fertiliser and enterprises with higher risks (Cai, 2016; Karlan et al., 2014). Investing in risk-increasing inputs and enterprises tend to be naturally associated with higher returns. Taking up agricultural insurance not only lead to increased incomes, but also decreases income fluctuations (de Nicola, 2015). Other studies report of less distress sales of productive assets when farmers purchase agricultural insurance (Janzen & Carter, 2018), reduced incidence of food insecurity (Karlan et al., 2014) and improved child health and subjective well-being (Jensen et al., 2018; Tafere et al., 2019).

Despite these potential benefits, agricultural insurance uptake remains low in most developing countries (Ali et al., 2020; Gine et al., 2008). This apparent puzzle has attracted numerous studies that seek to improve our understanding of the underlying causes. While a strand of both theoretical and empirical literature has explored imperfections in factor markets, in particular, the credit markets as key in driving the low uptake (Cole et al., 2013; Karlan et al., 2014), there have been increasing attention to behavioural factors in recent times (Belissa et al., 2020; Bryan, 2019).

We study the agricultural insurance uptake decisions by developing a model to show how risk and ambiguity preferences, and liquidity constraints relate to uptake decisions. Then, using recent survey and field experimental data on cocoa farmers from Ghana, we specify the sign and magnitude of the relationship.

The widespread information asymmetries and transaction costs have hindered the development of traditional insurance products in developing economies (Gunnsteinsson, 2020). To address these challenges, the index-based products where pay-outs depend on an exogenous and often publicly observable metric has been proposed and implemented. Yet, uptake remains puzzlingly low (between 5–24%), despite substantial subsidies (Karlan et al., 2014).

Many studies have argued that liquidity constraints often limit poor farmer's ability and willingness to take up agricultural insurance (Cole et al., 2013; Karlan et al., 2014). In recent times, however, a number of studies have explored not only the available resources at the disposal of poor farmers, but also the time the insurance products are made available (Belissa et al., 2020; Casaburi & Willis, 2018). An interesting observation is the highly cyclical nature of farmers' incomes, where they tend to have adequate financial resources during harvest periods, but these resources significantly decrease at the onset of the new planting season during which farmers purchase other inputs. Incidentally, most insurance products are sold at the onset of the planting season, thereby constraining take-up decisions. This makes the issue of liquidity constraints non-trivial in insurance participation decisions.

Behavioural factors including risks and ambiguity also play relevant roles in agricultural insurance uptake decisions. While risks characterise uncertainties with known probabilities of occurrence, the probabilities of occurrence in the case of ambiguity are unknown. In fact, insurance markets exist because individuals are willing to trade-off their production risks in expectation that their losses will be indemnified. Thus, the risk-averse farmers are expected to purchase agricultural insurance. However, the nature of index-based insurance is such that farmers need to simultaneously make decisions on two stochastic processes. First, the farmer needs to take into consideration the probability of incurring losses. Second, whether the index that triggers payment accurately reflects his or her losses, thus creating a compound probability event. Budescu and Fischer (2001) point out that most individuals fail to reconcile these two events. The compound lottery nature of index-based insurance uptake decisions often makes it difficult for individuals to decide on the basis of objective probability. Thus, cognition failure in reconciling the compound probability, in part, may be a cause for the low demand for index-based insurance (Elabed & Carter, 2015).

Similarly, the sheer lack of trust in receiving payments in case farmers incur losses further cast doubts on agricultural insurance (Belissa et al., 2020; King & Singh, 2020). Thus, insurance uptake decisions of farmers are driven not only by the highest expected utility, conditional on risk aversion, but also on the fact that insurance often involves ambiguity, such that the probabilities of potential outcomes are unknown (Barham et al., 2014; Bryan, 2019). In analysing the role of risks on farmers' demand for crop insurance, recent studies have argued that the impact of risks needs to be isolated from ambiguity (e.g. Belissa et al., 2020; Bryan, 2019).

Previous studies that assess the effects of risks and ambiguity on crop insurance uptake have either been largely empirical (e.g. Belissa et al., 2020), or where the authors incorporate theory (e.g. Elabed & Carter, 2015 and Bryan, 2019), they failed to incorporate the role of liquidity constraints. Unlike Elabed and Carter (2015) and Bryan (2019), we incorporate liquidity constraints in our theoretical model. This is particularly relevant in a developing country context where liquidity constraints appear to be perverse due to the poorly functioning credit markets (Ding & Abdulai, 2020). This presents a more comprehensive view to agricultural insurance purchasing decision typical of developing country context. Furthermore, unlike Bryan

(2019) who examined the uptake of a new crop variety as the main outcome variable, we present a different perspective, where the insurance product is our main outcome variable. This presents a different pathway to analyse the role of risk and ambiguity preferences on insurance uptake, devoid of other technologies that could potentially confound our outcome of interest.

Since there are no crop insurance programs in Ghana, we use field experiments to elicit farmers' risk preferences and ambiguity aversion, as well as their willingness to participate in crop insurance programs. We then employ discrete choice models to analyse the factors that drive farmers' decisions to participate in crop insurance. Given the lack of reliable historical data on the effect of rainfall patterns on cocoa production to inform the use of weather-index insurance, we focus on area-yield insurance.

The paper is structured as follows. The next section presents the theoretical model, while section 3 outlines the empirical strategy employed in the paper. Section 4 describes the data employed in the analysis. Section 5 discusses the empirical results. The final section contains conclusions and policy recommendations.

2. Theoretical model

In this section, we develop a model that analyses the effects of risk and ambiguity, liquidity constraints and input use on the demand for crop insurance. Our theoretical model builds on the earlier work by Horowitz and Lichtenberg (1993). We focus on the case of yield insurance, as considered in the empirical part of the study. To concentrate on the most important driving factors of the behavioural model, we consider a farmer who owns one hectare of land covered by productive cocoa trees. The opportunity cost or rental price of the land is denoted by p_h. In order to focus on yield variations, we assume that the market price of cocoa, p, as is the case in Ghana, is fixed for a one-year period. To simplify the model, different commonly applied inputs are represented by a generic input, denoted by the variable x, with a unit price of p_x. Cocoa production can be described by the per hectare production function $f(x,\epsilon)$, where ϵ denotes the part of production that varies with the random state of nature (Horowitz & Lichtenberg, 1993). The probability distribution of ϵ is denoted by $H(\epsilon)$ and the density function by $h(\epsilon)$, where ϵ can be considered as a productivity-index, dependent on factors such as temperature, rainfall, relative humidity, hours of sunshine and pest populations. The index can be ordered from the most adversarial $\epsilon_{\min}$ to most favourable $\epsilon_{\max}$ conditions for cocoa production. We assume that production can be described by a strictly concave production function $f(x,\epsilon)$, with $f_x \lesseqgtr 0, f_\varepsilon > 0$ and $f_{ii} < 0$, $f_i, f_{ii} \in C^2$, $i = x, \varepsilon$, where the subindex of the production function with respect to one of its arguments denotes the corresponding partial derivative. The yield $q = f(x, \varepsilon)$ is bounded by $q \in [q_{\min}, q_{\max}]$.

We consider the case where farmers have the option to insure their crop yields against all-risk with coverage $\gamma \in [0, 1]$.[1] The coverage γ indicates the percentage of the average yield $\overline{q}$ that is covered by the insurance, where $\gamma = 0$ indicates no insurance coverage at all, and $\gamma = 1$ the complete coverage of the average yields. The actual yield $q = f(x, \varepsilon)$, with $q \in [q_{\min}, q_{\max}]$ can be observed by the insurer. It is assumed that average yields $\overline{q}$ are determined by a third party and individual farmers cannot influence this reference point. The price of the yield insurance with coverage γ is denoted by $p_i(\gamma)$, with $p_i(\gamma) = 0$. If the actual yield is below the average yield insured, farmers receive indemnity payments. The paid indemnity is given by $\max[p(\gamma(\overline{q} - f(x, \varepsilon))), 0]$, which indicates that if the actual yield is less than the insured yield, then an indemnity is paid to the farmer, which is equal to the difference between the actual yield and the insured yield, multiplied by a pre-agreed sum per unit of yield (Bryla-Tressler et al., 2011). Under such an insurance contract, there exists a state of nature $\varepsilon^{\gamma} = \varepsilon^{\gamma}(x, \gamma\overline{q})$ defined by the implicit function $\gamma\overline{q} = f(x, \varepsilon^{\gamma})$, so that farmers receive an indemnity payment if ϵ falls below ϵ^{γ} (Babcock & Hennessy, 1996). The term ϵ^{γ} activates an indemnity payment, but ϵ^{γ} depends on the choice of x, so that the indemnity payment is also influenced by the farmer's choice of input x.

Given that many smallholder farmers in sub-Saharan Africa face liquidity constraints, we assume here that a farmer maximises expected utility, subject to liquidity constraints. Let us denote the farmer's net benefit by v, and the associated utility function by $u(v;r)$, with $u(\cdot) \in \mathbb{C}^2$ and r is a parameter that expresses the risk preferences. If the actual yield is below $\gamma\overline{q}$, the farmer's net benefits are given as $\nu^{\gamma} = p\gamma\overline{q} - p_x x - p_h - p_i(\gamma)$, otherwise, the net benefits are given by $\nu = pf(x, \varepsilon) - p_x x - p_h - p_i(\gamma)$. We consider farmers to be non-liquidity constrained through their own resources, if the price of the insurance coverage $p_i(\gamma)$ is lower than the share δ of expected net benefits, that is $\delta(E[\nu^{\gamma} + \nu]) - p_i(\gamma) > 0$. Farmers may be liquidity constrained through their own resources, but could still contract insurance coverage, if they have access to credit. In the theoretical part of the analysis, we focus on the concept of liquidity constraints by farmers' own resources, since the concept of credit constraints is to a large extent beyond their sphere of influence. The more general concept of credit constraints will be addressed in the empirical part of this study.

Considering the concept of liquidity constraints by own resources, the maximisation of the expected utility can be formulated as.

$$\max_x E[U] = \max_x E[u(\tilde{\nu}^{\gamma};r) + u(\tilde{\nu};r)] \tag{1}$$

where U stands for the expression $u(\tilde{\nu}^{\gamma};r) + u(\tilde{\nu};r)$ that is influenced by the risk preferences r. If the actual yield is below $\gamma\overline{q}$, the farmer's net benefits taking

[1] Independent of the coverage, the yield insurance does not cover damages or losses of the crop or tree itself.

into account the liquidity constraints are denoted by $\tilde{\nu}^{\gamma}$ and are given by $\tilde{\nu}^{\gamma} = \nu^{\gamma} + \mu(\delta(E[\nu^{\gamma} + \nu]) - p_i(\gamma))$ where μ denotes the Lagrange multiplier associated with the farmer's liquidity constraint. If the actual yield is above $\gamma\overline{q}$, the farmer's net benefits taking into account the liquidity constraint are denoted by $\tilde{\nu}$ and are given by $\tilde{\nu} = \nu + \mu(\delta(E[\nu^{\gamma} + \nu]) - p_i(\gamma))$.

Expected utility theory assumes that an agent is indifferent between two lotteries as long as the expected utilities are identical. However, the Ellsberg (1961) paradox illustrates that agents often prefer lotteries with known probabilities to those with unknown probabilities. The paradox can be considered as ambiguity aversion, which can be thought of as an aversion to any mean-preserving spread in the space of probabilities. On the other hand, risk aversion is considered as aversion to any mean-preserving spread in the space of the states (yields in our context), and not in the space of the probabilities. The information available to the agent is so imprecise to be summarised in a probability measure and the term ambiguity serves as a substitute. It is expressed by a second-order prior probability distribution over the set of plausible (first order) distributions. Gilboa and Schmeidler (1989) propose incorporating ambiguity aversion in the decision process by computing the expected utility of the farmer´s net benefits, conditional on each possible first-order prior probability distribution and evaluating the expected utilities at their minimum. Then, the authors propose choosing the maximal farm net benefits of all 'worst-case outcomes'. Agents who behave according to this maxmin model can be described as pessimists, since they focus on the downside probabilities. A smooth version of this maxmin expected utility model with multiple priors has been proposed by Klibanoff et al., (2005). They propose a monotically increasing function φ that weights the expected utility of the farm net benefits over the first-order prior probability distribution $h(\epsilon)$. The weighting process based on the second-order priors $\theta(h(\epsilon))$ can be seen as a second-order probability distribution (Machina & Siniscalchi, 2014). If the function φ is linear, it represents ambiguity neutrality, implying that the farmer is indifferent between decisions whose probability of outcomes is known compared to one with an unknown probability. However, a concave φ represents ambiguity aversion, in which case the farmer dislikes decisions characterised by unknown probabilities. Mathematically, the ambiguity corrected expected utility of the farmer´s net benefits is given by.

$$\int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi(E(U);\rho)\, d\theta(h(\varepsilon)) \tag{2}$$

where the parameter ρ denotes the individual ambiguity attitude. Equation (2) suggests that maximisation of the expected utility of the farmer's net benefits would not be affected if the agent were ambiguity neutral. In this case, the evaluation of the integral presents the maximised expected utility, since it is averaged over the second-order priors. Thus, if the utility function is concave, but the ambiguity function is linear, the agent is risk-averse, but not ambiguity averse. To analyse the effect of ambiguity preferences on farmers´ decisions, we determine the farmer´s optimal input choice from the first-order condition

$$\frac{d}{dx}\left(\int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi(E(U);\rho)d\theta(h(\varepsilon))\right) = \int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi'(E(U);\rho)\frac{d}{dx}E(U)d\theta(h(\varepsilon)) = 0 \tag{3}$$

Equation (3) shows that the ambiguity attitude and the risk preferences influence the optimal input choice. However, if the marginal value of the ambiguity function is constant, then the ambiguity attitude, in contrast to the risk preferences, does not affect the optimal choice of the input x.

To analyse the effect of a change in input use on the insurance coverage decision, we employ the implicit function theorem on equation (3) to obtain.

$$\frac{d\gamma\overline{q}}{dx} = \frac{-\int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi''(E(U);\rho)\left(\frac{\partial E(U)}{\partial x}\right)^2 + \varphi'(E(U);\rho)\frac{\partial^2 E(U)}{\partial x^2}d\theta(h(\varepsilon))}{\int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi''(E(U);\rho)\frac{\partial E(U)}{\partial x}\frac{\partial E(U)}{\partial \gamma\overline{q}} + \varphi'(E(U);\rho)\frac{\partial^2 E(U)}{\partial x \partial \gamma\overline{q}}d\theta(h(\varepsilon))} > 0 \tag{4}$$

However, without further specification of the employed functions, little further insight about the sign of the change in demand for insurance as a result of a change in input use can be obtained. As noted by Machina and Siniscalchi (2014), the isolation and empirical determination of the function φ is not possible, as it is intertwined with the utility function.[2] Even if we assume linear ambiguity preferences, the sign of the integral can only be determined for specific cases depending on the risk preferences, liquidity constraints, and whether inputs are risk-increasing or not. The same problem arises if we employ equation (3) to derive the demand for insurance as a result of a change in the risk preferences, $\frac{d\gamma\overline{q}}{dr}$, or in the ambiguity attitude, $\frac{d\gamma\overline{q}}{d\rho}$. For this reason, we do not attempt to determine the sign of the integral of the expressions $\frac{d\gamma\overline{q}}{dx}$, $\frac{d\gamma\overline{q}}{dr}$ and $\frac{d\gamma\overline{q}}{d\rho}$, but rather analyse the impact of input use, ambiguity aversion and risk preference on the demand for insurance coverage in the empirical part of the study.

[2] The expression $\varphi(E(U;r);\rho)$ is a composite function and for the evaluation of the integral, it is necessary to find its antiderivative, making it difficult for analytical solutions.

3. Empirical specification

In line with the maximisation problem in equation (1), the crop insurance decision problem can be formulated as.

$$U_{\gamma}^{**} \equiv \max_{\gamma} \int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi\Big(E\Big(U_{\gamma}^{*}\Big);\rho\Big) d\theta(h(\varepsilon)),\ subject\,to\,\delta E[\nu^{\gamma}+\nu] > p_i(\gamma). \quad (5)$$

where $U_{\gamma}^{*} = \max_{x} E[U(\nu^{\gamma}) + U(\nu)]$. Farmers who are liquidity constrained in equation (5) tend to choose the option with a lower γ, so that liquidity constraints is not binding. That is, the share of the expected net benefits (with and without coverage) decreases, making $\delta E[\nu^{\gamma}+\nu] < p_i(\gamma)$ a non-binding term in the maximisation problem. Equation (5) provides the basis for a specification for estimating farmers' crop insurance uptake decisions in the presence of liquidity constraints, either by own or external resources. Thus, given equation (5), and the above theoretical analysis, farmers' crop insurance decisions can be specified as

$$U_i^{**} = U(\text{risk and ambiguity preferences, prices, input use,}$$
$$\text{liquidity constraints, wealth}) \quad (6)$$

Specification (6) indicates that farmers' crop insurance uptake decisions will be affected by farm and household characteristics, as well as ambiguity and risk aversion. To the extent that wealth and the magnitude of possible losses and gains tend to influence farmers' insurance uptake decisions, in opposing directions, the question regarding which of the two effects dominate will be investigated in the analysis. In particular, the model reveals that farmers will be willing to participate in crop insurance if the expected utility of net benefits is positive. However, to the extent that the expected net benefits from uptake of crop insurance is unobservable, since it is subjective, we estimate a reduced-form specification, rather than a structural equation because of additional assumptions which are inconsistent with our data (Low & Meghir, 2017).

To formalise, if we denote the expected net benefits from participation as I_i^*, then $I_i^* > 0$ implies that the expected net benefits from uptake exceed that of non-participation. Although I_i^* is not observable, it can be expressed as a function of observable elements, such that crop insurance uptake decision is conditioned on the factors outlined in equation (6). These include prices, risk and ambiguity preferences, as well as farm and household-level characteristics and white noise. This can be specified as.

$$I_i^* = \alpha Z_i + \beta p(\gamma) + \mu_i \qquad I_i = 1\left[I_i^* > 0, I_i = 0 \ \ otherwise\right], \tag{7}$$

where I_i is a binary indicator variable that equals one if the farmer i is willing to contract a crop insurance coverage γ and zero otherwise. The terms α and β indicate vectors of parameters to be estimated, Z is a vector of farm and household-level characteristics, $p(\gamma)$ is the insurance premium and μi the error term.

Incorporating risk and ambiguity preferences into the discrete choice model explaining farmers' crop insurance uptake decisions specification in (7) yields:

$$I_i^*(\gamma) = \alpha Z_i + \beta p(\gamma) + \psi C_i + \eta G_i + \nu_i \qquad I_i = 1\left[I_i^* > 0, I_i = 0 \ \ otherwise\right], \tag{8}$$

where C_i represents a vector of risk preferences, and G_i, a measure of ambiguity preferences, with their respective parameters ψ and η to be estimated, and v_i is the error term. All the other variables and parameters are as defined earlier in equation (7).

The household-level variables within the vector Z_i include gender, age and education of the farmer, awareness of insurance, trust and liquidity constraints. The farm-level variables within the vector Z_i include total land owned, and fertiliser expenditure by the cocoa farmer and location dummies to capture location-specific effects. Of these variables, liquidity constraints and input use variables may be potentially endogenous. As argued by Carter et al., (2016), insurance can crowd-in credit, as farmers with insurance incomes pose less risk to creditors. Thus, purchasing insurance could in fact be driving farmers' access to credit and liquidity constraints status. Similarly, there is strong evidence to suggest that when farmers are insured, they tend to exert less effort and may also apply lower amounts of chemical inputs (Babcock & Hennessy, 1996). Other omitted variables including rates of time preference could as well be driving both the input use and insurance purchasing decisions. To address the potential endogeneity of the liquidity constraints and input use variables, we employed the control function approach (Wooldridge, 2015). This involves estimating first-stage determinants of fertiliser expenditure and liquidity constraints specifications, using Tobit and Probit models, respectively. The residuals from these estimations are then included in the second-stage Probit model of the willingness to take up crop insurance. Given that the two-stage estimation may lead to wrong estimates of the standard errors in the second stage, we bootstrapped the standard errors to account for the step-wise estimation (Andresen, 2018). The first-stage estimates for the three different models to be explained below are available upon request.

Most crop insurance studies have reported a positive correlation for education (e.g. Giné et al., 2008). Awareness, knowledge and understanding of the intricacies of insurance policy tend to influence the decision of farmers to participate in crop insurance programs (Hill et al., 2013). Most non-participants in crop insurance lack understanding of the insurance products (Giné et al., 2008) and, as Garrido and Zilberman (2008) rightly point out, the non-awareness of the benefits from crop insurance may limit farmers' participation in these programs. The general level of trust, may be associated with farmers' trust in receiving payments from insurance agents in the event of crop failure, is expected to have a positive effect on farmers' willingness to participate in the insurance program. Wealth, represented by total land owned, is expected to have a positive influence on the willingness to participate in crop insurance programs, since wealthier farmers have the financial means to purchase insurance (Sherrick et al., 2004).

As argued earlier, liquidity-constrained farmers normally find it difficult to purchase agricultural inputs and crop insurance (Croppensted et al., 2003). Farmers facing liquidity constraints to purchase inputs normally can relax the constraint by seeking credit from formal or informal sources. However, if farmers fail to obtain sufficient credit, they remain liquidity constrained. We therefore classified farmers as liquidity-constrained, if over two farming seasons they had financial constraints in purchasing farm inputs, and therefore, (1) attempted to obtain credit from formal or informal sources at the prevailing interest rate, but were unsuccessful; (2) obtained credit, but expressed interest in borrowing more at the prevailing interest rate, but did not succeed. The theoretical section indicated that input use is expected to have a positive impact on the willingness to participate in crop insurance programs.

4. Data description

The survey was conducted in the three largest cocoa-producing regions in Ghana, at the farm household level between April and July 2018. The regions include Ashanti, Brong-Ahafo and Western. The Western region is currently the largest cocoa-producing region in the country with more than 50 per cent of the total annual cocoa production, with Ashanti being the second largest producing region, followed by the Brong-Ahafo (Anim-Kwapong & Frimpong, 2009).

Prior to the survey, focus group discussions were held with farmers in the surveyed regions to understand their risks perceptions and the kinds of conditions that could result in lower than expected yields and reduced revenues. We also collaborated with the Ghana Agricultural Insurance Pool (GAIP), Ghana Insurers Association (GIA) and Ghana Cocoa Board (COCOBOD) in the design of the crop insurance products.

Stratified random sampling approach was used to select 750 cocoa-producing households. To ensure proportional representation, four districts were selected from the Western region and two districts each from Ashanti and Brong-Ahafo regions. The selected districts in Western are the Aowin, Sefwi-Akontombra, Sefwi-Juaboso and Bia West. Ahafo-Ano North and

Bosome-Freho districts were selected in Ashanti region, while Asunafo South and Dormaa East formed our study districts in the Brong-Ahafo region. In particular, 360 households were randomly sampled across 12 villages in the Western and 203 and 187 households across 6 villages each in Ashanti and Brong-Ahafo, respectively.

Farmers participated in field experiments after we collected data on their household and farm-level characteristics. The experimental part sought to measure four attitudinal variables, including farmers' risk and ambiguity preferences with monetary incentives. Four balls of similar size, but different colours; red, yellow, blue and green were put in an opaque box and shuffled for subjects to randomly pick a ball. The colour of the ball picked formed the basis for payment in one of the four games subjects played. Subjects' final due payment was disclosed and paid upon completion of the entire field experiment. We believe this served as an incentive for farmers to make choices as they would in the real-world situation.

Following Marenya et al., (2014), we used the stochastic dynamic game to elicit farmers' risk preferences. Subjects played in a three-session game, one at a time, without knowing the point of termination. In the first session of the game, farmers were presented with the option of choosing to participate in one of two gambles, **A** and **B**. In gamble **A**, farmers had the option to receive GH₵ 20 with certainty, or to participate in picking a red ball from an opaque box containing 5 red and 5 blue balls in **B**. If a red ball is successfully picked, the farmer receives GH₵ 40 instead. However, if a blue ball is picked, the farmer does not receive any money. In the second session, we maintained the certain amount, **A**, at GH₵ 20, and successfully picking a red ball in the lucky dip, **C**, resulted in GH₵ 24, a 40% reduction in the favourable outcome. Failing to pick a red ball resulted in no monetary payments. The third session came with **A** still fixed at GH₵ 20, and an increase in the favourable outcome to GH₵ 56 in the lucky dip **D** (see Table S1). We emptied the box and counted the balls each time a new farmer appeared at the experimental table. Based on farmers' choices in the three sessions, they are uniquely categorised into highly risk-averse, moderately risk-averse, risk neutral and risk loving.

Table 1 presents the distribution of risk preference categories. About 42.40% of the subjects were classified as highly risk-averse, 20.13% as moderately risk-averse, 6.13% as risk neutral and 29.33% as risk loving risk categories. A relatively small number of farmers (2.00%) made inconsistent choices, and as such could not be classified under any of the risk preference categories.

To also capture farmers' ambiguity aversion, we used field experiments. The ambiguity game set-up is presented in Table S3. We employed the method of elicitation by using two boxes, one containing 10 balls, where the number of red or blue coloured balls was unknown (Box **B**). The other box, **A**, however, contained known numbers of red and blue balls in the series of 6 games. For a prize of GH₵ 20, farmers were asked to choose between box **A** and **B**, where the share of the winning ball, red, in box **A** was gradually

Table 1 Basis for categorising risk preferences

Choices	Risk preference category	Frequency (%)
AAA	Highly risk averse	318 (42.40%)
AAD	Risk averse	151 (20.13%)
BAA	Risk neutral	46 (6.13%)
BCD, ACD	Risk loving	220 (29.33%)
BCA, ACA, BAD	Inconsistent choices	15 (2.00%)
Total		750 (100%)

Note: Risk attitudes were elicited by asking household heads to choose between a certain (riskless) amount of GH₵ 20 and a series of risky options with values GH₵ 40, GH₵ 24 and GH₵ 56, at a 50% probability.

reduced during the series of the games from an initial 100% to 0%. The probability of winning for box **B** remained unknown to the farmer as they had no knowledge on the number of red balls in each of the six games. Conditional on the box chosen, the farmer goes ahead with drawing. If the farmer succeeds in drawing a red ball, he or she wins the prize of GH₵ 20, otherwise, no payment is made. We based our categorisation of farmers' ambiguity aversion on their decision on the box from which they draw the ball. Specifically, a farmer is categorised as ambiguity averse, if he or she chooses a risky option instead of an ambiguous one with probability less than 50% ($p < 0.5$)We have chosen this point of reference as farmers prefer to accept adverse odds compared to unknown odds. Based on their choices made, about 57% of the farmers were categorised as being ambiguity averse (see Table 2).

To obtain information on willingness to participate in crop insurance programs, we used contingent valuation method by asking farmers whether they were willing to participate in the insurance program by randomly drawing from insurance premiums of GH₵ 100, GH₵ 120 and GH₵ 150 to minimise the incidence of starting point bias. We used responses from this for our subsequent analysis. In line with the Ghana Agricultural Insurance Pool (GHAIP), the premium rate was fixed at 10% of the liability. The liability was calculated by $p_i\gamma\overline{q}$, where p_i is the projected price, γ is the coverage and $\overline{q}$ is the average historical district yield. The average historical yield data obtained from COCOBOD were detrended using a weighted moving averages for its superior performance to other detrending methods (Ye et al., 2015). In particular, we used the 3-year lag, as it falls within the recommended 3–5 years.

We acknowledge the existence of a more promising incentive-compatible method such as the Becker-DeGroot-Marschak (BDM) that appears to encourage subjects to reveal their dominant strategy by bidding their true maximum (Berry et al., 2020), we, nevertheless, resorted to using the take-it-or-leave-it (TIOLI) approach for two reasons. First, the BDM mechanism requires the existence of the product for subjects to bid in a real-world situation (Voelckner, 2006). In our study, we did not have the insurance

Table 2 Descriptive statistics of variables used in the regression models

Variables	Variable description	Mean	SD
WIP	1 if farmer is willing to participate in the insurance, 0 otherwise	0.70	0.46
Premium	Price of insurance per acre (GHC)	121.80	20.77
Age	Age of household head (years)	52.06	12.59
Gender	1 if farmer is female, 0 otherwise	0.25	0.44
Read & write	1 if farmer can read and write 0, otherwise	0.49	0.50
VSLS	1 if farmer is a member of village Savings and loans association	0.15	0.35
Savings Account	1 if farmer has an active savings account, 0 otherwise	0.14	0.34
Shocks	1 if household experienced shock(s) in the last 3 years, 0 otherwise	0.08	0.28
Trust people	1 if generally trust in people, 0 otherwise	0.28	0.45
Highly risk-averse	1 if farmer is highly risk averse, 0 otherwise	0.42	0.49
Risk averse	1 if farmer is moderately risk averse 0 otherwise	0.20	0.40
Risk neutral	1 if farmer is risk neutral, 0 otherwise	0.06	0.24
Risk loving	1 if farmer is risk loving, 0 otherwise	0.29	0.46
Inconsistent choice	1 if farmer made inconsistent Choices, 0 otherwise	0.02	0.14
Ambiguity averse(AA)	1 if farmer is ambiguity averse, 0 otherwise	0.57	0.50
Aware of Insurance	1 if aware of any Insurance, 0 otherwise	0.22	0.41
Farm size	Farm size in acres 0 otherwise	8.58	9.22
Soil quality perception	1 if farmer perceives farm as good, 0 otherwise	0.53	0.50
Farm distance	Distance of from house to farm (km)	2.75	3.05
Fertiliser Exp.	Fertiliser expenditure per acre (GHC)	66.62	100.72
Liquidity constraint	1 if farmer is liquidity constrained, 0 otherwise	0.39	0.49
Total land owned	Total agricultural land owned (acres)	13.76	18.57
Western	1 if farmer is located in the Western region, 0 otherwise	0.48	0.50
Ashanti	1 if farmer is located in the Ashanti Region, 0 otherwise	0.27	0.44
Brong-Ahafo	1 if farmer is located in Brong-Ahafo Region, 0 otherwise	0.25	0.43

Note: Exchange rate: 1 US$ = GH₵ 4.73 in August 2018.

product that farmers could purchase and be compensated in the event that the metric triggers payment. Second, the BDM generally appears to be more complex to be undertaken in a field experimental conditions, particularly in a developing country context.

Prior to administering the questionnaires, we organised brief information sessions to farmers in groups not exceeding 10 members. Here, we explained the concept of area-yield insurance using Figure S2. During the group meetings, we addressed all queries that farmers raised to ensure they understood it. We further made provision for farmers to ask questions during the personal interview sessions.

In this study, farmers' willingness to participate in crop insurance is measured as a [0,1] dummy variable. Although stated preference methods are often limited in the study of actual behaviour, they are important sources of information on factors likely to influence uptake decisions, given that insights could be gained into how farmers react to changes in premiums (Hill et al., 2013). Given that the contingent valuation approach was a hypothetical experiment, we used a 'cheap talk' script to reduce hypothetical bias (Bello & Abdulai, 2016). This involved informing the participants to make their choices like they would, if facing these choices in their actual purchase decisions.

The descriptive statistics of the variables used in the empirical analysis are presented in Table 2, while the mean differences between the relevant variables are given in Table 3.

The results show that farmers willing to take up crop insurance programs tend to be proportionately more risk and ambiguity averse, less liquidity constrained, can read and write, trust people, and spend more on farm inputs.

Table 3 Absolute mean differences for farmers willing to participate and non-participants

Variables	Willing to participate $n = 524$ [70%]	Not willing to participate $n = 226$ [30%]	Abs. Mean Diff.
Premium	106.51 (19.54)	134.07 (18.22)	17.56***
Highly risk averse	0.49 (0.50)	0.27 (0.44)	0.23***
Risk averse	0.23 (0.42)	0.12 (0.33)	0.11***
Risk neutral	0.05 (0.21)	0.09 (0.29)	0.05**
Risk loving	0.21 (0.41)	0.49 (0.50)	0.28***
Inconsistent choices	0.02 (0.13)	0.03 (0.16)	0.01
Ambiguity averse (AA)	0.54 (0.02)	0.64 (0.48)	0.09**
Liquidity constraint	0.36 (0.48)	0.46 (0.50)	0.09**
Fert. expenditure per acre (log)	1.44 (0.73)	1.25 (0.77)	0.19***
Gender	0.23 (0.42)	0.31 (0.16)	0.07**
Awareness of Insurance	0.26 (0.44)	0.12 (0.33)	0.14***
Total land owned	14.81 (21.06)	11.32 (10.43)	3.49**
Trust people	0.32 (0.47)	0.18 (0.38)	0.14***
VSLS	0.16 (0.37)	0.11 (0.31)	0.05*
Savings account	0.14 (0.35)	0.12 (0.33)	0.02
Shocks	0.11 (0.01)	0.03 (0.01)	0.07***
Farm distance	2.65 (3.08)	2.97 (2.98)	0.32
Soil quality perception	0.52 (0.02)	0.54 (0.03)	0.03
Western	0.51 (0.50)	0.41 (0.49)	0.11***
Ashanti	0.25 (0.44)	0.31 (0.46)	0.06*
Brong-Ahafo	0.23 (0.42)	0.29 (0.45)	0.05

Note: Standard deviation values are in parentheses.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

5. Empirical results

Table 4 below presents estimates from the parsimonious specifications that examine the impacts of key variables on the willingness to participate in crop insurance. The variables include the insurance premium, risk aversion, ambiguity aversion, liquidity constraints and fertiliser expenditure.

While column 1 presents estimates from the specification with insurance premium and risk preferences as covariates, the results in column 2 contain that of ambiguity aversion and the premium. Estimates of liquidity constraints and the premium are in column 3, while columns 4–6 contain estimates of various combinations of these key variables.

As expected, the coefficients of the variable representing insurance premium are all negative and statistically significant in columns 1–6, indicating that the willingness to participate decreases with increasing premium. This finding is consistent with rational behaviour, where the demand for normal doods decline with increasing prices. The estimates for the coefficients of risk preferences, liquidity constraints and the level of fertiliser expenditure variables are individually consistent with our theoretical model, in the sense that the likelihood of participating in crop insurance programs appears to be positively correlated with risk attitudes and fertiliser expenditure, but negatively related to liquidity constraints. Even though we could not explicitly determine the sign of the effects of ambiguity aversion on insurance uptake decisions in the theoretical model, the empirical estimates appear to show a strongly negative relationship. These estimates provide insights into how farmers who dislike making decisions characterised with substantial uncertainties tend to be less willing to participate in crop insurance programs.

In Table 5, we present the expanded probit estimates of the model of willingness to participate in crop insurance, where we include covariates such as trust, farm characteristics, some individual characteristics and regional level dummies. The estimates show that the residuals from the results of the first-stage liquidity constraints and fertiliser expenditure specifications are not statistically significant, suggesting that the coefficients have been consistently estimated (Woodridge, 2015). As expected from the theoretical model, the empirical results show that farmers who are risk-averse (both high and moderate) tend to be more willing to participate in crop insurance programs, even with the inclusion of the previously stated covariates. Although the coefficient of risk-loving farmers is not statistically significant, it has the expected negative sign, an observation that is consistent with our theoretical prediction. These results are quite intuitive in that while the risk-averse farmer is willing to trade-off the risks associated with production, the risk-seeking are willing to retain their production risks. Our results are in line with the notion that risk-averse farmers relative to risk-neutral farmers, normally tend to hedge against potential income losses by increasing their demand for crop insurance.

Table 4 Parsimonious models of the effects of risk and ambiguity aversion on willingness to participate in crop insurance

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Premium	−0.0247***	−0.0261***	−0.0264***	−0.0246***	−0.0249***	−0.0250***
	(0.0026)	(0.0025)	(0.0025)	(0.0026)	(0.0026)	(0.0026)
Highly risk-averse	0.7060***	—	—	0.692***	0.7285***	0.821***
	(0.2135)	—	—	(0.2147)	(0.2155)	(0.1095)
Risk-averse	0.6425***	—	—	0.6486***	0.7239**	0.849***
	(0.2322)	—	—	(0.2334)	(0.2354)	(0.2209)
Risk loving	−0.1297	—	—	−0.1297	−0.1120	−0.0975
	(0.2146)	—	—	(−0.2157)	(0.2162)	(0.2201)
Inconsistent choice	0.2112	—	—	0.2070	0.2051	0.286
	(0.3998)	—	—	(0.4021)	(0.4014)	(0.4085)
Ambiguity averse(AA)	—	−0.2397**	—	−0.2119**	−0.2049*	−0.2053*
	—	(0.1039)	—	(0.1074)	(0.1081)	(0.1095)
Liquidity constraints	—	—	−0.2816***	—	−0.3502***	−0.2563**
	—	—	(0.1043)	—	(0.3502)	(0.1126)
Fertiliser expenditure(log)	—	—	—	—	—	0.1361***
	—	—	—	—	—	(0.0319)
Constant	3.2409***	3.9103***	3.9238***	3.3586***	3.4979***	2.9814***
	(0.3842)	(0.3259)	(0.3267)	(0.3904)	(0.3951)	(0.4138)
McFadden R^2	0.188	0.134	0.135	0.192	0.203	0.223
Likelihood (χ^2)	172.46	121.90	123.85	176.37	186.69	205.10
Deg. of freedom	5	2	2	6	7	8
Observations	750	750	750	750	750	750

Note: Standard errors are parentheses.
$^{***}p < 0.01$,
$^{**}p < 0.05$,
$^{*}p < 0$.

Table 5 Expanded model of the effects of risk preferences, ambiguity aversion and liquidity constraints on insurance participation

	Model 1		Model 2		Model 3	
	Coefficient	Marg. Eff.	Coefficient	Marg. Eff.	Coefficient	Marg. Eff.
Premium	−0.0265***	−0.0082***	−0.0272***	−0.0087***	−0.0263***	−0.0081***
	(0.0030)	(0.0010)	(0.0024)	(0.0008)	(0.0029)	(0.0009)
Ambiguity averse(AA)	—	—	−0.1934*	−0.0616*	−0.1401	−0.0430
	—	—	(0.1078)	(0.0345)	(0.1175)	(0.0362)
Highly risk-averse	0.8825***	0.2565***	—	—	0.8687***	0.2526***
	(0.2029)	(0.0554)	—	—	(0.2302)	(0.0635)
Risk-averse	0.8599***	0.2139***	—	—	0.8555***	0.2130***
	(0.2301)	(0.042)	—	—	(0.2618)	(0.0517)
Risk loving	−0.1181	−0.0372	—	—	−0.1207	−0.0379
	(0.1829)	(0.0587)	—	—	(0.2393)	(0.0763)
Inconsistent choice	0.3821	0.1019	—	—	0.3746	0.1002
	(0.3679)	(0.0834)	—	—	(0.3735)	(0.0951)
Liquidity constraints	−0.4327***	−0.1378***	−0.3444**	−0.1132**	−0.4271***	−0.1358***
	(0.1668)	(0.0529)	(0.1402)	(0.0463)	(0.1601)	(0.0522)
Fertiliser expenditure(log)	0.0912**	0.0282**	0.0549	0.0177	0.0937**	0.0289**
	(0.0439)	(0.0138)	(0.0564)	(0.0182)	(0.0428)	(0.0132)
Gender	−0.2043	−0.0654	−0.0436	−0.0141	−0.1966	−0.0628
	(0.1268)	(0.0412)	(0.1248)	(0.0408)	(0.1380)	(0.0449)
Age	−0.0082	−0.0025	−0.0073*	−0.0023*	−0.0079	−0.0025
	(0.0055)	(0.0017)	(0.0044)	(0.0014)	(0.0052)	(0.0016)
Read and write	0.3922***	0.12069***	0.3512***	0.1126***	0.3923***	0.1207***
	(0.1249)	(0.0379)	(0.1092)	(0.0356)	(0.1389)	(0.0437)
Awareness of insurance	0.5013***	0.1385***	0.5260***	0.1515***	0.5087***	0.1402***
	(0.1579)	(0.0458)	(0.1462)	(0.0388)	(0.1361)	(0.0319)
Trust	0.3372***	0.0984***	0.1319***	0.1116***	0.3392**	0.0990**
	(0.1212)	(0.0318)	(0.1251)	(0.0372)	(0.1709)	(0.0471)
Total land owned	0.0096**	0.0029**	0.0101**	0.0033**	0.0028**	0.0029**
	(0.0045)	(0.0014)	(0.0044)	(0.0014)	(0.0045)	(0.0013)
Fertiliser expenditure residual	−0.1719	−0.0532	−0.1441	−0.0464	−0.16904	−0.0523

Table 5 (*Continued*)

	Model 1		Model 2		Model 3	
	Coefficient	Marg. Eff.	Coefficient	Marg. Eff.	Coefficient	Marg. Eff.
	(0.1195)	(0.0370)	(0.1127)	(0.0364)	(0.1057)	(0.0334)
Liquidity constraint residual	−0.0695	−0.0215	−0.0440	−0.01420	−0.0585	−0.0181
	(0.1587)	(0.0491)	(0.1788)	(0.0576)	(0.1501)	(0.0466)
Constant	3.6847***	—	4.2775***	—	3.7198***	—
	(0.6779)	—	(0.5905)	—	(0.7100)	—
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
McFadden R^2	0.282	—	0.203	—	0.284	—
Wald (χ^2)	227.66***	—	243.69***	—	285.33***	—
Deg. of freedom	17	—	14	—	18	—
Observations	750	—	750	—	750	—

Note: Bootstrapped standard errors are in parentheses.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

The estimates, shown in Table 5 reveal that farmers who tend to be averse to uncertainties without known probabilities of occurrences are less likely to participate in the insurance programs (model 2). Based on these estimates, it may be inferred that perhaps farmers could be anchoring priors on the distribution of their cocoa yield losses from experiences in cocoa farming. However, mentally stimulating whether the index may trigger payment could be cognitively challenging. This additional uncertainty characterising the area-yield insurance may be driving farmers who are averse to ambiguous outcomes to decrease their willingness to take up the insurance programs. These estimates suggest that when farmers are less informed on the probability of outcomes of the insurance program, they tend to be cautious in their decision to participate. The findings are consistent with the results reported by Bryan (2019) in his recent study on a sample of farmers from three African countries. However, it is relevant to note that the inclusion of risk preference variables resulted in statistically insignificant coefficients of the ambiguity variables (model 3 in Table 5).

Regarding the estimates in Table 5, the coefficient of the variable representing liquidity constraints is negative and significantly different from zero, suggesting that farmers facing liquidity constraints are less likely to participate in crop insurance programs (Croppensted et al., 2003). When farmers are liquidity constrained, premium payments would be more expensive for them, because of lack of adequate financial resources prior to income receipts after crop harvests. Thus, liquidity constraints do not only limit the purchase of inputs for production purposes, but also play a relevant role in decreasing the tendency for farmers to participate in insurance programs. These findings are in line with the results from Casaburi and Willis (2018), who found that liquidity constraints mattered in farmers' demand for insurance in Kenya.

Our empirical results further show that farmers spending more on fertiliser have a higher tendency to participate in crop insurance programs. This is not surprising, given that the economic benefits of fertiliser application are often contingent on the random state of nature, particularly on timely rainfall. In a bad state of nature, applying chemical fertiliser will further reduce farmers' expected profits, because the crops will not make use of the applied fertiliser for productive gains. However, in a good state of nature, farmers' expected profits increase. Therefore, applying chemical fertiliser increases the variation in the expected profits. It is not surprising that farmers whose spending are relatively high on chemical fertilisers will be more willing to participate in the insurance programs to hedge against this variation in expected profits.

The results of the estimates of interaction of risk preferences and ambiguity aversion on insurance uptake decisions are presented in Table 6.

Column 1 presents estimates of risk and ambiguity preferences, as well as liquidity constraints and fertiliser expenditure, while in column 2 estimates of these variables and other covariates are presented. The results from the first column indicate that even though the effects of ambiguity aversion on its own

Table 6 Interaction effects of risk and ambiguity aversion, and fertiliser expenditure on the probability of participation in crop insurance

Variable	Model 1		Model 2	
	Coefficient	Marg. Efft.	Coefficient	Marg. Efft.
Premium	−0.0252***	−0.0081***	−0.0262***	−0.0081***
	(0.0026)	(0.0008)	(0.0026)	(0.0008)
Ambiguity averse(AA)	−0.5449	−0.1693	−0.5763	−0.1714
	(0.3910)	(0.117)	(0.3914)	(0.1117)
Highly risk-averse	0.5020	0.1562	0.5343	0.1591*
	(0.3310)	(0.0989)	(0.3308)	(0.0943)
Risk-averse	0.6688*	0.1836**	0.7286*	0.1872**
	(0.3859)	(0.0871)	(0.3308)	(0.0799)
Risk loving	−0.3486	−0.3486	−0.4246	−0.1383
	(0.3304)	(0.3304)	(0.3375)	(0.1152)
Inconsistent choice	0.2466	0.0727	0.4352	0.1129
	(0.5263)	(0.1406)	(0.5126)	(0.1076)
AA* Highly risk-averse	0.4325	0.1272	0.5657	0.1538
	(0.4318)	(0.1433)	(0.4389)	(0.1029)
AA * Risk-averse	0.1394	0.0431	0.2282	0.0659
	(0.4809)	(0.1433)	(0.4912)	(0.1319)
AA * Risk loving	0.3867	0.1132	0.4934	0.1337
	(0.4326)	(0.1139)	(0.4359)	(0.1016)
AA * Inconsistent choice	−0.0579	−0.0189	−0.0937	−0.0298
	(0.7489)	(0.2493)	(0.7216)	(0.2368)
Liquidity constraints	−0.3747***	−0.1231***	−0.4381***	−0.1391***
	(0.1337)	(0.0446)	(0.1402)	(0.0451)
Fertiliser expenditure(log)	0.1679***	0.0539***	0.0973**	0.0300**
	(0.0412)	(0.0132)	(0.0474)	(0.0147)
Gender	—	—	−0.1982	−0.0632
	—	—	(0.1369)	(0.0449)
Age	—	—	−0.0079	−0.0025
	—	—	(0.0051)	(0.0016)
Read and write	—	—	0.3899***	0.1196***
	—	—	(0.1251)	(0.0379)
Awareness of insurance	—	—	0.5067***	0.1393***
	—	—	(0.1577)	(0.0374)
Trust	—	—	0.3323**	0.0968***
	—	—	(0.1345)	(0.0367)
Total land owned	—	—	0.0097**	0.0029**
	—	—	(0.0042)	(0.0013)
Fertiliser expenditure residual	—	—	−0.1628	−0.0502
	—	—	(0.1018)	(0.0314)
Liquidity constraint residual	—	—	−0.0407	−0.0126
	—	—	(0.1424)	(0.0439)
Constant	3.7182***	—	3.9554***	—
	(0.5791)	—	(0.6719)	—
Regional fixed effects	No	No	Yes	Yes
McFadden R^2	0.228	—	0.286	—
Wald χ^2	177.73***	—	198.73***	—

Table 6 (*Continued*)

Variable	Model 1		Model 2	
	Coefficient	Marg. Efft.	Coefficient	Marg. Efft.
Deg. of freedom	14	—	15	—
Observations	750	—	750	—

Note: AA refers to ambiguity aversion; Bootstrapped standard errors are in parentheses; Risk neutral is the reference category for risk preference.
$^{***}p < 0.01$,
$^{**}p < 0.05$,
$^{*}p < 0.1$.

are qualitatively similar to our previous estimates, it is not statistically significant. Regarding estimates of integration of ambiguity aversion with risk aversion, the sign changed to positive, suggesting that perhaps the effect of risk aversion dominate that of ambiguity aversion in influencing insurance uptake decisions. This may be indicative that risk preferences have sufficiently large effects on farmers' decision to participate in insurance programs relative to ambiguity aversion. Contrary to Barham et al., (2014), who found risk aversion to have relatively low effects relative to ambiguity aversion on the adoption of new technology, our results show strong impact of risk preferences on insurance uptake decisions.

Other statistically significant variables include farmers' ability to read and write, as well as the variable representing farmers' general level of trust in people. The positive sign of influence for farmers' ability to read and write is consistent with most crop insurance studies, suggesting that literate farmers are more likely to participate in crop insurance programs (Hill et al., 2013). Trust, which is a social capital variable, plays a relevant role in farmers' participation decisions in insurance programs. Farmers who generally trust people are more willing to participate in crop insurance programs, because they tend to trust that they would receive the compensation in the event of crop failures (Casaburi & Willis, 2018).

Awareness of insurance programs shows a positive effect, confirming the proposition that farmers with knowledge on insurance are more likely to participate in crop insurance programs (Giné et al., 2008). The positive and significant coefficient of the variable representing total land owned increases the probability of participation in crop insurance programs. These findings are in line with the notion that crop insurance is a normal good, with demand increasing with wealth (Clarke, 2016).

6. Conclusions

In this study, we developed a model to examine the role of risk and ambiguity aversion, and liquidity constraints on crop insurance uptake decisions among cocoa farmers in Ghana. Given the lack of crop insurance programs in the country, we used field experimental methods to elicit farmers' willingness to participate in area-yield insurance programs, and lotteries to capture farmer' risk and ambiguity aversion. We then employed discrete choice models to analyse how household and farm-level factors, as well as risk and ambiguity aversion, tend to influence the willingness to participate in crop insurance programs.

We showed in the theoretical analysis that risk and ambiguity aversion, as well as liquidity constraints, can significantly influence farmers' decisions to participate in crop insurance programs. The results from the empirical analysis revealed that insurance premium has a negative influence on farmers' willingness to participate in the programs, indicating that insurance is a normal good, with demand declining with increasing prices. We also found that those farmers who were risk-averse are more likely to participate in crop insurance programs compared to the risk-loving farmers, confirming the significance of risk preferences in farmers' willingness to participate in crop insurance. However, even though ambiguity-averse farmers were less willing to participate, we did not find significant changes in our empirical estimates upon interacting it with their risk preferences. These findings suggest that policymakers need to take into consideration farmers' risk preferences when introducing crop insurance programs to help them accurately predict farmers' participation decisions.

From a policy perspective, the government and other actors can leverage on the available mobile technologies to make yield data easily accessible to farmers. This will, in particular, be relevant for ambiguity-averse farmers in forming priors about particular states of the yield distribution. Their averseness to extreme events may be reduced to improve participation. Government can also enact regulations to deal with extreme negative outcomes, which has often been the underlying cause of ambiguity aversion. Regulations on these 'left tail' events could be particularly helpful in minimising the ambiguity, and improving uptake of index-based insurance product.

The results revealed that farmers facing liquidity constraints are less likely to participate in crop insurance programs, suggesting that the problem of financial constraints is not confined to the purchase of farm inputs, but also a hindrance to participation in crop insurance programs. These findings confirm that the current efforts by both non-governmental organisations and governmental financial intermediaries to improve farmers' access to credit at reasonable rates are measures that need to be intensified. This is particularly important in helping farmers to overcome financial barriers in their agricultural production decisions, especially in the purchase of farm inputs and in enhancing farmers' participation in crop insurance programs. As argued by Casaburi and Willis (2018), participation in crop insurance programs could be promoted in sub-Saharan African through measures that relax liquidity constraints facing poor farmers, such as deferred payments until harvest season where they are less liquidity constrained. With the high penetration of mobile payment platforms in Africa, policies could be formulated to encourage the telecommunication networks and financial institutions to strengthen their relationship to make their credit facilities accessible and on timely basis.

The empirical results also revealed positive and significant impacts of farmers' ability to read and write on willingness to take up crop insurance. From a policy perspective, this indicates that providing farmers with a clearer understanding on how crop insurance works through training and workshops would increase their awareness and subsequent uptake of crop insurance programs. To the extent that crop insurance is a way of hedging against yield and income losses from adverse weather conditions occurring from climate change, supporting farmers to participate in insurance programs could help farmers stabilise their incomes. Moreover, it is significant to mention that smallholder farmers need an insurance package that is suited to their specific needs and characteristics and that future research could aim at designing such insurance packages.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Supplementary Material