Liquidity constraints, risk preferences and farmers' willingness to participate in crop insurance programs in Ghana

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Abstract

This paper analyzes smallholder farmers' decisions to participate in crop insurance programs, using cross-sectional data from cocoa farmers in the Ashanti, Brong-Ahafo and Western Regions of Ghana. Given the significance of output uncertainty and imperfect capital and insurance markets, we develop a theoretical framework to show how risk preferences and liquidity constraints influence farmers' crop insurance participation decisions. We use a 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 and liquidity constraints influence farmers' willingness to participate in crop insurance programs. The results also show that the probability of participating in crop insurance programs is higher for males, the more educated, and those who trust others. The levels of fertilizer and pesticide expenditure and the access to credit are also found to significantly influence the decision to adopt the programs.

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1. Introduction

Interests in crop insurance in sub-Saharan Africa has been growing over the past decade in response to the prospect of new programs and policy changes that promise to confer positive net economic benefits to participating producers. The production patterns of participants in insurance programs tend to be affected when their incentives are altered by such economic benefits (Just et al., 1999). Particularly in, livelihoods and developmental aspirations of many countries, agricultural insurance has been suggested as one of the potential channels for mitigating agricultural production risks, and stabilizing income fluctuations of smallholder farmers (Sarris, 2002; Miranda and Farrin, 2012; Smith and Glauber, 2012).

However, because of widespread asymmetric information, in particular, moral hazard and adverse selection problems, agricultural insurance markets remain underdeveloped in sub-Saharan Africa (Karlan et al., 2014). The Africa Agriculture Status Report (AASR) from 2017 indicates that while globally agricultural insurance is a US$2 billion business, Africa accounts for less than two percent of the market (AGRA, 2017). Moral hazard normally occurs when farmers are able to influence losses because their farming practices cannot be accurately monitored by insurers. Adverse selection, which has been regarded as the more significant reason for the low adoption rates of farmers, occurs when farmers with higher probabilities of losses face higher expected returns from adoption, and therefore tend to be more likely to adopt than their counterparts with lower probabilities of losses (Smith and Baquet, 1996).

Weather-index insurance—where pay-outs depend only on observable rainfall realizations—has been proposed as a way of dealing with the problems of moral hazard and adverse selection in crop insurance markets in developing countries (e.g., Elabed et al., 2013; Karlan et al., 2014). Several studies have therefore analyzed farmers' willingness to participate in crop insurance programs in developing countries (Giné et al., 2008; Hill et al., 2013; McIntosh et al., 2013; Sarris, 2013; Karlan et al., 2014).). Many of these studies have revealed that farmers generally prefer ideal insurance with no basis risk contracts relative to contracts with basis risk, such as weather-index insurance, particularly when these two types of insurance contracts are similar in terms of expected values and possible alternatives (e.g., Marenya et al., 2014).

Participation in crop insurance programs is closely related to the issue of imperfect capital and insurance markets in low-income countries. A number of studies have shown that imperfect credit markets tend to influence farmers' demand for agricultural inputs and crop insurance (e.g., Giné et al., 2008; Binswanger-Mkhize, 2012; Farrin and Miranda, 2013; Karlan et al., 2014). In particular, the low utilization of agricultural inputs in sub-Saharan Africa has been partly attributed to market failures such as liquidity constraints, imperfect competition, lack of information and risk coping strategies on crop failure that often distort input markets and discourage farmers from using them (Dorward, 2009). Differential access to capital thus plays a crucial role in explaining observed differences in the use of chemical inputs and demand for agricultural insurance by smallholder farmers in many developing countries (Binswanger-Mkhize, 2012; Farrin and Miranda, 2013; Karlan et al., 2014). Some authors have indicated that when farmers are liquidity constrained, they often trade-off returns for reduced risk, making them unable to purchase agricultural insurance (Binswanger-Mkhize, 2012; Hill et al., 2013). In particular, Binswanger-Mkhize (2012) argued that poor farmers who are not well insured and could benefit from purchase of insurance tend to be severely cash and credit constrained, making it impossible for them to translate potential demand into purchases. Casaburi and Willis (2018) have recently shown in their study on Kenya that liquidity constraints matter in poor farmers' decisions to purchase crop insurance.

A number of studies have therefore examined the relationship between chemical input use and adoption of crop insurance programs (Smith and Goodwin, 1996; Babcock and Hennessy, 1996; Wu, 1999; Goodwin et al., 2004). Smith and Goodwin (1996) have argued that because farmers sometimes purchase farm inputs before making decisions on crop insurance programs, the causal relationship between the two decisions remains an empirical issue, while Wu (1999) has indicated that if insurance encourages the shift toward crops with more demanding input requirements, then adoption of crop insurance programs may actually increase fertilizer usage.

In this study, we contribute to the literature on demand for crop insurance by developing a theoretical model to link liquidity constraints, risks preferences and input use to farmers' willingness to participate in crop insurance programs. To the extent that data on crop insurance purchase decisions are not available in Ghana, we use a choice experiment framework to obtain information on farmers' decisions to participate in crop insurance programs, and then analyze the factors that influence this participation decisions. We focus on area-yield insurance for cocoa farmers in Ghana, instead of weather-index-based schemes. Unlike for food crops, there are currently no reliable historical data on the effect of rainfall patterns on cocoa production. For effective design and implementation of crop insurance programs, data on climate, agronomy of the crop, production and pricing must be available, accessible, consistent and reliable (Burke et al., 2010).

The rest of 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 analyzes the effects of risks attitudes, input demand, and liquidity constraints 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 a yield insurance, as considered in the empirical part of the study. To concentrate on the most important driving factors of the behavioral model, we consider a farmer that owns 1 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 is constant and denoted by p.[1] The cultivation of cocoa trees requires employing different inputs such as machinery, labor, fertilizer or pesticides. To simplify the model, these different inputs are represented by a generic input, denoted by the variable x, with unit price of p_x. Cocoa production can be described by the per hectare production function $f(\mathrm{x},\varepsilon)$, where ε denotes the part of production that varies with the random state of nature (Horowitz and Lichtenberg 1993). The probability distribution of ε is denoted by $H(\varepsilon)$ and the density function by $h(\varepsilon)$, 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 adversable $\varepsilon_{\min}$ to most favorable $\varepsilon_{\max}$ conditions for cocoa production. We assume that production can be described by a strictly concave production function $f(x,\varepsilon)$, 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 $\gamma \in [0,1]$.[2] The coverage γ indicates the percentage of the average yield $\bar{q}$ 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 $\bar{q}$ 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 $p_i(0) = 0$. If the actual yield is below the average yield insured, farmers receive indemnity payments. The paid indemnity is given by $\max\left[p\left(\gamma\bar{q} - f(x,\varepsilon)\right), 0 \right]$, 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 $\varepsilon^{\gamma} = \varepsilon^{\gamma}(x, \gamma\bar{q})$ defined by the implicit function $\gamma\bar{q} = f(x, \varepsilon^{\gamma})$, so that the farmers receive an indeminity payment if ε falls below ε^{γ} (Babcock and Hennessy 1996). The term ε^{γ} activates an indeminity payment, but ε^{γ} depends on the choice of x, so that the indemity payment is also influenced by the farmer's choice of input x. If the insurer is not able to perfectly observe ε, or write a contract contingent on x, the farmer may be tempted to exert less effort, resulting in a moral hazard problem. Similarly, if the insurer has incomplete information about the functions $f(\cdot)$ or $h(\cdot)$ when the contract is signed, the underwriter may face the adverse selection problem (Horowitz and Lichtenberg 1993).

Given that many smallholder farmers in sub-Saharan Africa face liquidity constraints, we assume here that a farmer maximizes expected utility, subject to a liquidity constraint. Let us denote the farmer's net benefit by ν, and the associated utility function by $u(\nu)$, with $u(\cdot) \in \mathbb{C}^2$. If the actual yield is below $\gamma\bar{q}$, the farmer`s net benefits are given $\nu^{\gamma} = p\gamma\bar{q} - p_x x - p_h - p_i(\gamma)$, otherwise, the net benefits are given by $\nu = pf(x,\varepsilon) - p_x x - p_h - p_i(\gamma)$. Farmers are considered non-liquidity-constrained by their own resources, if the price of the insurance coverage $p_i(\gamma)$ is lower than the share δ of expected net benefits, i.e. $\delta\left(E\left[\nu^{\gamma} + \nu\right]\right) - p_i(\gamma) > 0$, Albeit liquidity-constrained by their own resources, farmers can still contract insurance coverage, if they are not credit-constrained, i.e. they have sufficient access to credit to purchase the insurance coverage. In the theoretical part of the analysis, we focus on the concept of liquidity-constraint by own resources, since the concept of credit-constraint is to a large extent beyond their sphere of influence. The latter concept will be accounted for in the empirical part of this study. Thus, based on the concept of liquidity-constraints by own resources, the farmer maximizes the expected utility given by

$$\begin{aligned} & E\left[u\left(\nu^{\gamma}\right) + u(\nu)\right] + \mu\left(\delta\left(E\left[\nu^{\gamma} + \nu\right]\right) - p_i(\gamma)\right) = \\ & \int_{\varepsilon_{\min}}^{\varepsilon^{\gamma}} u\left(\nu^{\gamma}\right) h(\varepsilon)\, d\varepsilon + \int_{\varepsilon^{\gamma}}^{\varepsilon_{\max}} u(\nu) h(\varepsilon)\, d\varepsilon + \mu\left(\delta\left(\int_{\varepsilon_{\min}}^{\varepsilon^{\gamma}} \nu^{\gamma} h(\varepsilon)\, d\varepsilon + \int_{\varepsilon^{\gamma}}^{\varepsilon_{\max}} \nu h(\varepsilon)\, d\varepsilon\right) - p_i(\gamma)\right) \end{aligned} \tag{1}$$

where μ denotes the Lagrange multiplier associated with the farmer's liquity constraint. The first-order condition for the farmer yields

$$\begin{aligned} & -p_x u'\left(\nu^{\gamma}\right) H\left(\varepsilon^{\gamma}\right) + \int_{\varepsilon^{\gamma}}^{\varepsilon_{\max}} u'(\nu)\left(pf_x(x,\varepsilon) - p_x\right) h(\varepsilon)\, d\varepsilon \\ & + \mu\delta\left(-p_x H\left(\varepsilon^{\gamma}\right) + \int_{\varepsilon^{\gamma}}^{\varepsilon_{\max}} \left(pf_x(x,\varepsilon) - p_x\right) h(\varepsilon)\, d\varepsilon\right) = 0 \end{aligned}, \tag{2}$$

where $u'(\cdot)$ denotes the derivative of the utility function with respect to the net benefits. In the absence of a yield insurance, $\gamma = 0,$ we have that $\varepsilon^{\gamma} = \varepsilon_{\min}$ so that equation (2) in terms of the expected value operator can be written as

$$\begin{aligned} &E\left[u'(\cdot)\left(pf_x(\cdot)-p_x\right)\right]+\mu\delta E\left[pf_x(\cdot)-p_x\right]=0 \\ &E\left[u'(\cdot)\right]E\left[pf_x(\cdot)-p_x\right]+COV\left[u'(\cdot),pf_x(\cdot)\right]+\mu\delta E\left[pf_x(\cdot)-p_x\right]=0 \end{aligned} \tag{3}$$

For a risk neutral and non-liquidity constrained farmer, we observe that $u'(\cdot)$ is a positive constant and the term $\mu = 0$. Therefore, the first line of equation (3) only holds if $E\left[pf_x(\cdot)-p_x\right]=0$, the solution that indicates the optimal input use. It requires that the expected marginal benefits be equal to the marginal costs. If the farmer was risk-neutral, but liquidity-constrained, $\mu \neq 0$, the first line of equation (3) only holds if the term $E\left[pf_x(\cdot)-p_x\right]$ is strictly positive. It implies that a liquidity-constrained farmer will be expected to apply less inputs than a non-liquidity constrained farmer. Moreover, under these conditions, the first line of equation (3) can only be satisfied, if the shadow value of the liquidity constraint μ is negative. A negative shadow value is consistent with economic intuition, since it implies that some net benefits are expected to be lost as a result of a binding liquidity constraint.

If the farmer was risk-averse, the *COV* term in equation (3) would be negative. Thus, for a risk-averse and non-liquidity constrained farmer, $\mu = 0$, the second line of equation (3) can only be satisfied if the term $E\left[pf_x(\cdot)-p_x\right]$ were positive. It implies that a risk-averse farmer is expected to apply less inputs than a risk-neutral farmer. In the case that the risk-averse farmer were also liquidity-constrained, μ is strictly negative, so that $E\left[pf_x(\cdot)-p_x\right]$ has to be again positive, but greater than in the case of a non-liquidity-contrained farmer. The increase in

$E\left[pf_x(\cdot)-p_x\right]$ would imply that a risk-averse and liquidity-constrained farmer is expected to apply less inputs than a risk-averse, but non-liqudity constrained farmer. The liquidity constraint could also be considered in terms of a participation constraint, as known in the literature on principal agent models. Unfortunately, equation (3) does not allow considering the effect of a change in input use on the optimal contracted insurance coverage (participation), since it does not include the change in the marginal farm-net-benefits resulting from a change in input use. For this purpose, we revert to the notation used in equation (2). To analyze the effect of a change in input use on the insurance coverage decision, we employ the implicit function theorem on equation (2) to obtain

$$\frac{d\gamma\bar{q}}{dx}=\frac{-d\left(E\left[u\left(\nu^{\gamma}\right)+u\left(\nu\right)\right]\right)^{2}\Big/d^{2}x}{-pp_x u''\left(\nu^{\gamma}\right)H\left(\varepsilon^{\gamma}\right)-p_x u'\left(\nu^{\gamma}\right)h\left(\varepsilon^{\gamma}\right)\frac{d\varepsilon^{\gamma}}{d\gamma\bar{q}}-u'\left(\nu^{\gamma}\right)\left(pf_x\left(x,\varepsilon^{\gamma}\right)-p_x\right)h\left(\varepsilon^{\gamma}\right)\frac{d\varepsilon^{\gamma}}{d\gamma\bar{q}}}$$
$$+\frac{-d\left(E\left[u\left(\nu^{\gamma}\right)+u\left(\nu\right)\right]\right)^{2}\Big/d^{2}x}{\mu\delta\left(-p_x h\left(\varepsilon^{\gamma}\right)\frac{d\varepsilon^{\gamma}}{d\gamma\bar{q}}-\left(pf_x\left(x,\varepsilon^{\gamma}\right)-p_x\right)h\left(\varepsilon^{\gamma}\right)\frac{d\varepsilon^{\gamma}}{d\gamma\bar{q}}\right)} \tag{4}$$

Taking again the derivative of equation (2) with respect to x shows that

$$\frac{d\left(E\left[u\left(\nu^{\gamma}\right)+u\left(\nu\right)\right]\right)^{2}}{d^{2}x}=\left(p_x\right)^{2}u''\left(\nu^{\gamma}\right)H\left(\varepsilon^{\gamma}\right)+\int_{\varepsilon^{\gamma}}^{\varepsilon_{\max}}\left(u''(\nu)\left(pf_x(x,\varepsilon)-p_x\right)+u'(\nu)\,pf_{xx}(x,\varepsilon)\right)h(\varepsilon)\,d\varepsilon$$
$$+\mu\delta\int_{\varepsilon^{\gamma}}^{\varepsilon_{\max}}pf_{xx}(x,\varepsilon)h(\varepsilon)\,d\varepsilon<0,$$

if the expected net benefits are positive. Economic reasoning seems to support this assumption.

Rearranging equation (4) yields

$$\frac{d\gamma\bar{q}}{dx} = \frac{d\left(E\left[u\left(v^{\gamma}\right)+u\left(v\right)\right]\right)^{2} \Big/ d^{2}x}{u'\left(v^{\gamma}\right)\left[pf_{\varepsilon}p_{x}\frac{u''\left(v^{\gamma}\right)}{u'\left(v^{\gamma}\right)}\frac{H\left(\varepsilon^{\gamma}\right)}{h\left(\varepsilon^{\gamma}\right)}+\frac{\mu\delta\left(pf_{x}\left(x,\varepsilon^{\gamma}\right)\right)}{u'\left(v^{\gamma}\right)}+pf_{x}\left(x,\varepsilon^{\gamma}\right)\right]h\left(\varepsilon^{\gamma}\right)\frac{d\varepsilon^{\gamma}}{d\gamma\bar{q}}} \lesseqgtr 0 \tag{5}$$

The sign of $\frac{d\gamma\bar{q}}{dx}$ depends on the sign of the terms in square brackets of equation (5), since $\frac{d\varepsilon^{\gamma}}{d\gamma\bar{q}} = \frac{1}{f_{\varepsilon}} > 0$. The first term in the square brackets is either positive, if the farmer is risk seeking, $u'' > 0$, zero if the farmer is risk neutral, $u'' = 0$, or it is negative if the farmer is risk averse, $u'' < 0$. The second term is either zero if the farmer is not liquidity-constrained, $\mu = 0$, or negative if the farmer is liquidity constrained. The sign of the third term in the square brackets, $pf_{x}\left(\cdot\right)$, cannot be negative for all ε because it would violate the first-order condition (2). Thus, one can conclude that there exists at least one ε where $pf_{x}\left(\cdot\right)$ is positive. If $pf_{x}\left(\cdot\right)$ is positive for all ε, both arguments of the production function are complements, and x is a risk-reducing input. However, if $pf_{x}\left(\cdot\right)$ is negative at least for some ε, the two arguments of the production function are substitutes for these values of ε and x is a risk-increasing input. A typical example of this situation is the case where increases in the intensity of production lead to a higher susceptibility of pests or diseases.

For a risk-reducing input, equations (4) and (5) show that an increase in intensity leads to less demand for insurance coverage, $\frac{d\gamma\bar{q}}{dx} < 0$, if a non-liquidity-constrained farmer is either risk-seeking or risk-neutral. However, if the farmer is risk-averse and the input is risk-increasing, the sign of equation (5) is ambiguous. In the case where the absolute value of the risk-aversion coefficient $-\frac{u''}{u'}$ dominates the remaining terms in the square bracket, an increase in input use leads to an increase in the demand for insurance coverage. Similarly, for a risk-averse and non-liquidity-constrained farmer, an increase in a risk-increasing input results in a higher demand for insurance coverage. With the increase in input use the farmer's expected net-benefits increases which in turn favors an increase in the insurance coverage. In contrasts, if the input is risk-reducing, a non-liquidity-constrained farmer chooses to decrease insurance coverage if the marginal product of input-use is larger than the weighted effect of absolute risk-aversion (the first term of equation (5)). However, if the farmer is liquidity-constrained and cannot contract the additional insurance coverage $d\gamma\bar{q}$, the shadow value of the constraint indicates the forgone net benefits. In this case, the mid-term in the square brackets specifies together with the terms outside the square bracket the increase in insurance coverage of $d\gamma\bar{q}$, as a result of a hypothetical increase in input use. All three effects in the square brackets are also driven by the factors to the left and right of the square brackets. The factors to the right present the effect of an increase in the insurance coverage on the indemnity activating state of nature and the resulting change in density of this state of nature and the factors to the left of the square bracket, the marginal utility. The previous analysis gives rise to the following observation

Observation: *The demand for insurance coverage increases with inputs if the farmer is risk-averse or risk-neutral and inputs are risk increasing* $\left(f_x < 0 \right)$*, or if the absolute value of the negative risk-aversion coefficient dominates all other effects. The demand for insurance coverage decreases with inputs if a non-liquidity constrained farmer is risk-neutral or risk-seeking and inputs are risk-reducing, or if the value of the positive risk-aversion coefficient dominates all other effects.*

Though we did not consider the wealth of the farmer, which consists of farm and non-farm assets, it is widely documented in the literature (Mas Colell et al. 1995) that a concave utility function exhibits decreasing absolute risk aversion with increasing wealth. Thus, according to equation (5), one would expect that wealthy risk-averse and non-liquidity constrained farmers increase their demand for insurance coverage, with an increase in risk-increasing input-use more than non-wealthy farmers. However, if the input is sufficiently risk-reducing so that the denominator of equation (5) becomes positive for a wealthy farmer but not for a non-wealthy farmer, the demand of insurance coverage by a wealthy farmer reduces with an increase in input use. The empirical part of our study analyzes the effect of wealth on the willingness to participate in crop insurance programs. However, it needs to be noted that farmers may have different utility functions, so that their behavior is not only driven by differences in wealth, but also by differences in risk preferences.

In capturing risk preferences, our theoretical model focused on the effects of the mean and variance of production, but ignored aversion to unfavorable "downside risk" or loss aversion. However, the prospect theory suggests that farmers tend to focus on gains and losses, with wealth playing a minor role on the WTP (Kahneman and Tversky, 1979). For example, Harrison et al. (2010) in their work on Ethiopia showed that some households make decisions under uncertainty that are in line with cumulative prospect theory rather than expected utility theory. Exposure to downside risk implies being exposed to a higher risk of losses, as compared with the risk of occurrence of gains (Di Falco and Chavas, 2009). Farmers exhibiting downside risk aversion generally have incentives to invest in measures that reduce exposure to such risks. Both aspects of risk preferences will be examined in the empirical part of the study.

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

$$U_\gamma^{**} \equiv \max_\gamma \left[U_\gamma^*\right], \text{ subject to } \delta \mathrm{E}\left[\nu^\gamma + \nu\right] > p_i\left(\gamma\right). \tag{6}$$

where $U_\gamma^* = \max_x E\left[U(\nu^\gamma) + U\left(\nu\right)\right]$. Farmers that are not able to meet the liquidity constraint in equation (6) tend to choose the option with a lower γ, where the liquidity constraint is not binding. Equation (6) provides the basis for a specification that allows the estimation of farmers' willingness to participate in crop insurance programs in the presence of liquidity constraints, either by own or external resources. Thus, given equation (6), and the above theoretical analysis farmers' crop insurance decisions can be specified as

$$U_i^{**} = U \text{ (risk preferences, prices, input use, liquidity constraints, wealth).} \tag{7}$$

Specification (7) indicates that farmers' willingness to participate in crop insurance programs will be affected by farm and household characteristics, and risk preferences. To the extent that wealth and the magnitude of possible losses and gains tend to influence farmers' willingness to participate in crop insurance programs in opposing directions, the question regarding which of the two effects dominate will be a subject of investigation in the empirical part of the study. Similarly, the empirical part of the study will analyze the influence of input use, and liquidity constraints on the willingness to participate in crop insurance programs.

3. Empirical strategy

The theoretical model outlined above examines the impact of risks attitudes, liquidity constraints, and input use on farmers' willingness to participate in crop insurance programs. The model reveals that farmers' willingness to participate is influenced by farm and household level factors, as well as risk attitudes. In particular, the model reveals that farmers will be willing to participate in crop insurance, if the net expected utility of net benefits is positive. That is, if the expected utility of profit from participation is greater than that of non-participation. However, to the extent that the expected net benefits from participation is unobservable, since it is subjective, we estimate a reduced-form specification, rather than a structural equation.

To formalize, if we denote the expected net benefits from participation as I_i^*, then $I_i^* > 0$ implies that the expected net benefits from participation exceeds that of non-participation. Although I_i^* is not observable, it can be expressed as a function of observable elements, such that the decision to participate in crop insurance program is conditioned on prices, risk attitudes, as well as farm and household-level characteristics and white noise. This can be specified as

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

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 a vector of farm and household-level characteristics, $p(\gamma)$ is the insurance premium, and μ_i the error term.

We use field experimental approach to measure and categorize farmers into the various risk preferences groups. Incorporating the risk preferences into the discrete choice model explaining farmers' willingness to participate in crop insurance specification in (8) yields:

$$I_i^*(\gamma) = \alpha Z_i + \beta p(\gamma) + \psi C_i + \nu_i \qquad I_i = 1\left[I_i^* > 0, I_i = 0 \text{ otherwise}\right], \tag{9}$$

where C_i represents the vector of risk preferences, ψ a parameter to be estimated, and v_i captures the random effects. All the other variables and parameters are as defined earlier in equation (8).

As indicated above, Z is a vector of farm and household-level characteristics, such as gender, age and education of the farmer, awareness of crop insurance, participation in off-farm work and liquidity constraints. The farm-level variables include farm size, age of the cocoa plantation, fertilizer and pest expenditure by the cocoa farmer and location dummies to capture location specific effects. Of these variables, input use variables may be endogenous, because they may be jointly determined by other factors. The potential endogeneity of the input use is addressed by using the control function approach (Wooldridge 2015).

As indicated previously, we also used choices from a series of games in field experiment from the farmers to ascertain their risk attitudes. The categories of risk preferences are presented in Table 1. With this approach, the risk preference variables indicate whether the farmer is highly risk averse, moderately risk averse, risk neutral and risk loving. It must however be noted that there were a few farmers (2%) who made inconsistent choices. These risk preference categories are included in the probit model to examine their effects on willingness of the farmers to participate in crop insurance.

Most crop insurance studies have reported positive correlation for education (Sherrick et al., 2004; Giné et al., 2008; Hill et al., 2013). 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 those programs. The level of trust[3], which is 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 are not likely to be liquidity-constrained (Hill et al., 2013; Sherrick et al., 2004; Enjolras et al., 2012).

As argued earlier, liquidity-constrained farmers normally find it difficult to purchase agricultural inputs and crop insurance (Croppensted et al., 2003; McIntosh et al., 2013). 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 of the willingness to participate in crop insurance programs. The expenditures on fertilizer and pesticides are used as inputs in the specification.

4. Data description

Since data on crop insurance purchase decisions are not available in Ghana, we conducted a choice experiment survey to capture farmers' willingness to participate in crop insurance programs in the country. 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. Agriculture is the main economic activity in Ghana, and cocoa is the most important tree and cash crop (Ghana Tree Crop Policy, 2011). The Western region is currently the largest cocoa producing region in the country with more than 50 percent of the total annual cocoa production, with Ashanti being the second largest producing region, followed by the Brong-Ahafo (Anim-Kwapong and 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), Innovation for Poverty Action (IPA), Ghana Cocoa Board (COCOBOD) and the Ministry of Food and Agriculture (MoFA) in the design of the crop insurance products.

Based on information acquired from the regional agricultural offices, a stratified random sampling approach was used to select 750 cocoa producing households from the Ashanti, Brong-Ahafo and Western regions. To ensure proportional representation, four districts were selected from 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. While Ahafo-Ano north and Bosome-Freho districts were selected in Ashanti region, 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. In all, 750 households from 24 villages were sampled across the three leading cocoa producing regions.

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 preferences with monetary incentives.[4] Given the limited resource availability, we were only able to compensate farmers for one of the four experiments where they were going to take part in. To avoid a bias for the game they get paid for, we setup an initial game with four equally likely outcomes to determine in which of the experiments subjects will receive the monetary incentive. This information was conveyed to the participants, but they had no knowledge for which of the four games they get paid. Four balls of similar size but different colors; red, yellow, blue and green were put in an opaque box and shuffled for subjects to randomly pick a ball. The color 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 incentive for farmers to make choices as they would in the real world situation.

As in Marenya et al. (2014), we used the stochastic dynamic game to elicit farmers' risk preferences. Specifically, we used a two-stage dynamic game with payouts. 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, a participation in the lucky dip, **C**, resulted in GH₵ 24, a 40% reduction in expected value. Here again, 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 expected outcome to GH₵ 56 in the lucky dip **D** (see Table A1 in the appendix for game set-up). It must be emphasized that 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 categorized into highly risk averse, moderately risk averse, risk neutral and risk loving. Table 1 presents the distribution. From the table, about 56.5% of the subjects were highly risk-averse, 18.9% moderately risk-averse, 6% risk-neutral and 30% risk loving risk categories. A relatively small number of farmers (2.0%) made inconsistent choices during the 3 sessions.

To obtain information on willingness to participate in crop insurance programs, we used two approaches, First we employed a contingent valuation method farmers by asking farmers whether they were willing to participate in the insurance program by randomly varying the premiums of GH₵ 100, GH₵ 120 and GH₵ 150. We used responses from this for our subsequent analysis. This preceded the actual discrete choice experiment which in the interest of brevity, we do not present here, as the main focus of this paper is to examine farmers' willingness to participate in the insurance program at the actuarially fair prices and not necessarily their preferences for the various attributes of the insurance products.[5] In line with the Ghana Agricultural Insurance Pool (GHAIP), the premium rate was fixed at 10% of the liability. The liability was calculated by $p_i \gamma \bar{q}$, where p_i is the projected price, γ is the coverage, and $\bar{q}$ is the average historical district yield.

Relevant information was gathered through direct face-to-face interviews on household-level demographic and plot-level characteristics, household wealth and assets, farmers' awareness of crop insurance, and other relevant production data. In this study, a farmer's willingness to participate in crop insurance is measured as a [0,1] dummy variable, indicating one if the farmer expresses willingness to participate in the average-yield insurance programs, and zero otherwise. 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 participate in crop insurance programs tend to be less liquidity constrained, can better read and write, trust people, and spend more on farm inputs. As rightly noted by Hill et al. (2013), a major limitation of stated preferences methods that are not supported by actual insurance products is that they do not represent actual behavior. However, such studies are important sources of information on the factors that are likely to influence farmers' participation in crop insurance programs, and also provide insights into how farmers would react to changes in premiums of insurance products. Given that it was a hypothetical experiment, we used a "cheap talk" script to reduce hypothetical bias (Lusk, 2003). This involved instructing the participants to make their choices like they would if facing these choices in their retail purchase decisions.

5. Empirical results

As indicated previously, farmers' decision to participate or not to participate in the crop insurance program was captured with a dichotomous variable, taking values of one for willingness to participate and zero for non-participation. This crop insurance participation dummy is then regressed on farmers' risk preference variables, liquidity constraints and other household and farm specific variables. We focus on farmers' expenditures on fertilizer and pesticides in their input use. To the extent that input use expenditures could be potentially endogenous in the crop insurance participation decision, we controlled for it using the control function approach proposed by Wooldridge (2015). This involved the estimation of first-stage determinants of fertilizer and pesticide expenditures specifications, using Tobit models. The residuals from these estimations were then included with the observed values of the variables into the probit model of willingness to participate in crop insurance. The first-stage estimates are presented in Table A1 in the appendix.

Table 4 presents the probit estimates of the model of willingness to participate in crop insurance, where the covariates premium, risk preferences, input use, liquidity constraints, trust are all included, with other variables. Both the coefficients and marginal effects of the variables are presented. The estimates show that the residuals from the results of the first-stage are not statistically significant, suggesting that the coefficients have been consistently estimated. As was 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 the crop insurance program. Although the marginal effect of risk-loving farmers is not statistically significant, it has the expected negative sign, an observation that is consistent with our theoretical prediction. 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. These empirical results are consistent with the findings in the theoretical model.

The marginal effect of the liquidity-constraint variable is negative and significantly different from zero, suggesting that farmers facing liquidity constraints have a lower probability of participating in crop insurance programs (Croppensted et al., 2003; Hill et al., 2013). This finding is in line with the results reported by Casaburi and Willis (2018), who found that liquidity constraints mattered in farmers' demand for insurance in Kenya. Consistent with the theoretical framework, the variables representing expenditure on fertilizer and pesticides both have positive and statistically significant effects on farmers' willingness to participate in crop insurance programs.

The estimated marginal effects of gender also show that females are less likely to participate in crop insurance. Other statistically significant variables include farmers' ability to read and write as well as the variable representing farmers' general level of trust in people.

Understanding the workings of insurance policies require considerable cognitive ability and therefore with higher level of education, which we measured with ability to read and write, had the expected positive and significant effect. The positive marginal effect for education is consistent with most crop insurance studies, suggesting that more educated farmers are more likely to participate in crop insurance programs (Mishra and Goodwin, 2006; Giné et al., 2008; Hill et al., 2013). Trust, which is a social capital variable, plays a relevant role in farmers' participation decisions on 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, a finding that is consistent with Casaburi and Willis (2018) study on insurance take-up in Kenya.

Awareness of agricultural insurance programs shows a positive marginal effect, confirming the preposition that farmers with knowledge on agricultural insurance are more likely to participate in crop insurance program (Gine et al., 2008). The positive and significant coefficient of the variable representing total land owned indicates that land ownership, which also represents wealth, increases the probability of participation in crop insurance programs, probably because such landowners are less likely to be liquidity constrained.

6. Conclusions

In this study, we develop a theoretical model to examine the impacts of risk preferences, liquidity constraints, and input use on smallholder farmers' willingness to participate in crop insurance programs in Ghana. Given the lack of crop insurance programs in the country, we used stated preference methods to elicit farmers' willingness to participate in area yield insurance programs. We then employ discrete choice models to analyze how household and farm level factors, as well as risks preferences tend to influence the willingness to participate in crop insurance.

We show in the theoretical analysis that risk preferences, risk-increasing or risk-reducing input use, and liquidity constraints can significantly influence farmers' willingness to participate in crop insurance programs. The results from the empirical analysis showed 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 friendly farmers, confirming the significance of risk preferences in farmers' willingness to participate in crop insurance. These findings suggest that policy makers need to take into consideration farmers' risk preferences when introducing crop insurance programs to help them accurately predict farmers' participation decisions.

We also found evidence that farmers facing liquidity constraints are less likely to adopt 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 of crop insurance programs. This finding confirms that the current efforts by both non-governmental organizations 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, rather than paying the entire premium upfront.

The empirical results also revealed positive and significant impacts of schooling, membership in farmers' organization and participation in off-farm work on farmers' decisions to participate in crop insurance programs. From a policy perspective, this indicates that providing farmers with clearer understanding on how crop insurance works through training and workshops would increase their awareness and subsequent uptake of crop insurance products. 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 stabilize 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 a package.

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Table 1: Basis for categorizing risk preferences

Choices made	**Risk preference category**	**Frequency (Percentage)**
AAA	Highly risk averse	326 (43.46%)
AAD	Risk averse	142 (18.93%)
BAA	Risk neutral	44 (5.86%)
BCD, ACD	Risk loving	223 (29.73%)
BCA, ACA, BAD	Inconsistent choices	15 (2.0%)
	Total	750 (100%)

Table 2. Descriptive statistics of variables used in the regression models

Variable	Variable description	Mean	S.d	Min	Max
WIP	1 if farmer is willing to participate in the insurance, 0 otherwise	0.70	0.46	0.00	1.00
Premium	Price of insurance per acre (GHC)	113.49	18.98	100.00	150.00
Age	Age of household head (years)	52.06	12.59	21.00	89.00
Gender	1 if farmer is female, 0 otherwise	0.25	0.44	0.00	1.00
Household size	Household size	5.90	2.92	1.00	22.00
Read & write	1 if farmer can read and write 0, otherwise	0.47	0.50	0.00	1.00
Children school	Number of children in school	2.85	2.10	0.00	13.00
Indigene	1 if farmer is an indigene, 0 otherwise	0.47	0.50	0.00	1.00
VSLS	1 if farmer is a member of village Savings and loans association	0.10	0.30	0.00	1.00
Cocoa cert	1 if member of cocoa certification, 0 otherwise	0.33	0.47	0.00	1.00
Trust	1 if generally trust in people, 0 otherwise	0.28	0.45	0.00	1.00
Highly risk-averse	1 if farmer is highly risk averse, 0 otherwise	0.43	0.50	0.00	1.00
Risk averse	1 if farmer is moderately risk averse 0 otherwise	0.19	0.39	0.00	1.00
Risk neutral	1 if farmer is risk-neutral, 0 otherwise	0.06	0.24	0.00	1.00
Risk loving	1 if farmer is risk loving, 0 otherwise	0.30	0.46	0.00	1.00
Inconsistent choice	1 if farmer made inconsistent Choices, 0 otherwise	0.02	0.14	0.00	1.00
Aware of Agric. Insurance	1 if aware of any agricultural Insurance, 0 otherwise	0.22 0.70	0.41 0.46	0.00 0.00	1.00
Farm size	Farm size in acres	8.58	9.22	1.00	150.00
Amelonado	1 if farmer planted Amelonado (Tetteh Quarshie) variety, 0 otherwise	0.06	0.24	0.00	1.00
Amazon	1 if farmer planted Amazon variety. 0 otherwise	0.73	0.44	0.00	1.00
Hybrid	1 if farmer planted Hybrid variety, 0 otherwise	0.20	0.40	0.00	1.00
Cocoa years	Age of cocoa plantation (years)	16.11	9.91	1.0	114.50
Fertilizer expenditure	Fertilizer expenditure per acre	63.64	127.87	0.00	1260.00

Pesticide expenditure	Pesticide expenditure per acre	69.08	78.71	0.00	892.75
Liquidity constraint	1 if farmer is liquidity constrained, 0 otherwise	0.35	0.48	0.00	1.00
Total land owned	Total agricultural land owned (acres)	13.76	18.57	0.00	335.00
Livestock value	Total value of livestock owned (‘000 GHC)	2.24	11.78	0.00	283.80
Off-farm work	1 if farmer participates in off-farm work, 0 otherwise	0.69	0.48	0.00	4.00
Western	1 if farmer is located in the Western region, 0 otherwise	0.48	0.50	0.00	1.00
Ashanti	1 if farmer is located in the Ashanti Region, 0 otherwise	0.27	0.44	0.00	1.00
Brong-Ahafo	1 if farmer is located in Brong-Ahafo Region, 0 otherwise	0.25	0.43	0.00	1.00

Exchange rate: 1 US$= GH¢ 4.73 in August 2018

Table 3: Mean differences for farmers willing to participate and those not willing

Variables	**Willing to participate** n=526 [70%]	**Not willing to participate** n=224 [30%]	**Abs. Mean Diff.**	**t-statistics**
Premium	105.86	131.43	-25.57***	21.45
	(12.77)	(19.12)		
Age of household head	51.60	53.14	1.54	1.54
	(11.94)	(13.96)		
Gender (female)	0.22	0.32	0.10***	2.81
	(0.42)	(0.47)		
Read and write	0.51	0.39	0.12***	3.00
	(0.50)	(0.49)		
Off-farm work	0.68	0.72	0.04	0.10
	(0.49)	(0.45)		
Total land owned	14.80	11.30	3.50**	2.27
	(21.04)	(10.40)		
Trust people	0.32	0.17	0.15***	4.21
	(0.47)	(0.38)		
Liquidity constraint	0.33	0.42	0.09**	2.49
	(0.47)	(0.49)		
Highly risk averse	0.50	0.28	0.23***	5.81
	(0.50)	(0.45)		
Moderately risk averse	0.23	0.09	0.14***	4.41
	(0.42)	(0.29)		
Risk neutral	0.04	0.10	0.06***	3.02
	(0.20)	(0.30)		
Risk loving	0.21	0.50	0.30***	8.47
	(0.41)	(0.50)		
Inconsistent choices	0.02	0.03	0.01	0.87
	(0.13)	(0.16)		
Awareness of Agric. Insurance	0.26	0.12	0.14***	4.30
	(0.44)	(0.33)		
Amazon	0.74	0.72	0.02	0.35
	(0.44)	(0.45)		
Hybrid	0.21	0.20	0.01	0.28
	(0.40)	(0.40)		
Amelonado (Tetteh Quarshie)	0.06	0.08	0.02	1.08
	(0.23)	(0.27)		
Fertilizer expenditure per acre	66.53	56.86	9.67	0.94
	(138.45)	(98.58)		
Pesticide expenditure per acre	71.37	63.70	7.67	1.22
	(78.03)	(80.20)		
Western	0.52	0.40	0.12***	3.02
	(0.50)	(0.49)		
Ashanti	0.25	0.32	0.07*	1.86
	(0.43)	(0.47)		
Brong-Ahafo	0.23	0.29	0.05	1.56
	(0.42)	(0.45)		

Standard deviation values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4. Probit estimates on farmers' willingness to participate in crop insurance

Variables	coefficient	marginal effect
Premium	-0.0556***	-0.0161***
	(0.0037)	(0.0013)
Age of household head	0.0532	0.0154
	(0.0378)	(0.0109)
Age squared	-0.0006	-0.0002
	(0.0004)	(0.0001)
Gender (female)	-0.2736	-0.0831
	(0. 1902)	(0.0610)
Read and write	0.3403**	0.09732**
	(0.1652)	(0.0047)
Off-farm work	0.1116	0.0322
	(0.1347)	(0.0391)
Total land owned	0.1466*	0.0423*
	(0.0819)	(0.0236)
Trust people	0.3627**	0.0977**
	(0.1543)	(0.0383)
Liquidity constraint	-0.3146**	-0.0940**
	(0.1350)	(0.0411)
Highly risk averse	0.7224***	0.1992***
	(0.2422)	(0.0623)
Moderately risk averse	0.9923***	0.2151***
	(0.2961)	(0.0439)
Risk loving	-0.2935	-0.0886
	(0.2399)	(0.0756)
Inconsistent choices	0.0691	0.0194
	(0.5025)	(0.1371)
Awareness of Agric. Insurance	0.5570***	0.1399***
	(0.1912)	(0.0394)
Amazon	0.6412***	0.2042***
	(0.2268)	(0.0771)
Hybrid	0.5372*	0.1346*
	(0.2796)	(0.0599)
Fertilizer expenditure per acre	0.0012*	0.0004*
	(0.0007)	(0.0002)
Fertilizer expenditure residual	0.0027	0.0008
	(0.0030)	(0.0009)
Pesticide expenditure per acre	0.0022***	0.0006***
	(0.0008)	(0.0002)
Pesticide expenditure residual	-0.0052	-0.0015
	(0.0054)	(0.0016)
Western	0.2625	0.0754
	(0.2759)	(0.0787)
Ashanti	-0.0378	-0.0110

	(0.1996)	(0.584)
Constant	4.2801***	
	(1.2220)	
McFadden R^2	0.48	
Wald $\chi^2(22)$	308.65***	
Number of observations	747	

Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Risk neutral is the base variable; Amelonado (Tetteh Quarshie) is the reference variable for variety

Appendix

Table A1: First-stage Tobit estimates of Input Use (Fertilizer and Pesticide) expenditures

	Model 1	Model 2
	Fertilizer Expenditure model	Pesticide Expenditure
Variables		
Age		-0.4733*
		(0.243)
Read and write	19.5284*	-13.9324**
	(11.562)	(6.029)
Gender	-30.1794**	-23.0695***
	(13.789)	(7.119)
Household size	6.6097**	
	(3.1619)	
Children_school	-8.3857**	
	(4.289)	
Indigene		22.1830***
		(5.939)
Farm size	-0.3842	-0.5505*
	(0.604)	(0.322)
Cocoa years		0.4814
		(0.5577)
Cocoa years squared		-0.0053
		(0.007)
Hybrid	37.2492***	12.0898
	(13.751)	(7.470)
Livestock value	0.9918**	
	(0.475)	
VSLS	46.815**	21.4543**
	(18.782)	(9.759)
Western	58.6843***	37.2967***
	(14.056)	(7.261)
Ashanti	-11.702	9.7768
	(15.730)	(8.086)
Constant	-14.4933	64.4667***
	(18.114)	(15.035)
Log-likelihood test	76.18***	65.92***
Degrees of freedom	10	12
Observations	750	

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A2: Experimental game for eliciting risk preferences

Game	Options			
	A		**B**	
Game 1	○	GH₵ 20 for certain	○	GH₵ 40 with 50% chance
	A		**C**	
Game 2	○	GH₵ 20 for certain	○	GH₵ 24 with 50% chance
	A		**D**	
Game 3	○	GH₵ 20 for certain	○	GH₵ 56 with 50% chance

End notes

[1] This is in line with the situation in Ghana, where cocoa prices are normally fixed for a one year period by the COCOBOD of Ghana.

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

[3] The level of trust was measured on a 5-point likert scale by asking farmers to generally indicate their level of (dis)agreement with the statement that most people can be trusted. Those who indicated that they strongly disagreed, disagreed and neutral were given a score of 0, while those who agreed or strongly agreed were scored 1.

[4] The other three attitudinal variables included loss aversion, ambiguity and trust. In this study, we focus on risk preferences.

[5] Since the focus of the current paper is not on examining farmers' preferences for the different crop insurance product attributes, but rather on the willingness of farmers to participate in crop insurance program, we do not elaborate in detail the choice experimental design. The main features of the crop insurance program options are the insurance claims describing the liability claims per hectare per annum, the insurance unit describing the management of the contract, indicating whether the policy is to be privately owned or government owned, the average coverage level specifying the percentage of farmers' yield losses they insure.