The Institute of Food Economics and Consumption Studies

of the Christian-Albrechts-Universität zu Kiel

Essays on Formal and Informal Risk Management in Agriculture: Behavioral Insights on Cocoa Farmers in Ghana

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutritional Sciences of the

Christian-Albrechts-Universität zu Kiel

Submitted by

M.Sc. Williams Ali

Born in Kumasi, Ghana

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Dedication

To my loving parents. They deserve great commendation for this achievement

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Abstract

One of the widely documented puzzles in the empirical economic literature is the co-existence of evidence of risk aversion, and the very low uptake of agricultural insurance among farmers in developing countries. Despite the growing body of evidence, studies on behavioral factors influencing agricultural insurance uptake decisions remain scant. This study investigates the drivers of the low agricultural insurance uptake, by paying particular attention to behavioral factors. Specifically, the first objective of the study is to comprehensively review the literature by showcasing the state of the art on agricultural insurance, as a risk management tool in developing countries. The second objective is to develop and test a theoretical model on how risk and ambiguity preferences, and liquidity constraints influence crop insurance uptake decisions. Third, the study examines the effects and implications of time preferences on crop insurance uptake decisions. The final objective is to assess the impact of rotating savings and credit association (ROSCA) on investment in farm inputs and welfare, using the marginal treatment effect (MTE) framework. Multiple techniques, including incentivized and unincentivized methods are employed to measure the behavioral factors in the field experiments. Also, since there are currently no crop insurance programs in Ghana, this study employed both contingent valuation methods and discrete choice experiments to examine the preferences and willingness to participate in the crop insurance programs. From the review of the voluminous studies, this study finds the lack of trust, liquidity constraints, the partial coverage of risks, the lack of understanding of insurance products, and some behavioral factors such as ambiguity and time preferences as the main drivers of the low uptake of agricultural insurance. The empirical analyses show that risk preferences, ambiguity aversion and liquidity constraints influence farmers' decision to participate in crop insurance programs. Furthermore, the probability of participating in crop insurance programs is positively influenced by wealth, trust and level of formal education. Interestingly, the empirical results also reveal that while

short-run measure of time preferences significantly decrease the demand for attributes of the crop insurance product, the long-run measure appears to enhance demand. Farmers also tend to favour insurance with delayed payments until harvesting. Lastly, the study finds that farmers with high propensity to participate in ROSCAS invest more in farm inputs, and earn significantly high farm incomes compared to non-participants. Under high incidence of shocks, ROSCAS participants increase investments in farm inputs and earn significantly higher farm incomes. From a policy perspective, while efforts are made to design a more suitable crop insurance program to increase uptake, informal institutions such as ROSCAS should not be relegated to the background.

Zusammenfassung

Eines der am häufigsten dokumentierten Rätsel in der empirischen Wirtschaftsliteratur ist die Koexistenz von Anzeichen für Risikoaversion und die sehr geringe Inanspruchnahme von landwirtschaftlichen Versicherungen durch Landwirte in Entwicklungsländern. Trotz der wachsenden Zahl von Belegen gibt es nur wenige Studien über Verhaltensfaktoren, die die Entscheidung über die Inanspruchnahme von landwirtschaftlichen Versicherungen beeinflussen. Die vorliegende Studie untersucht die Ursachen für die geringe Inanspruchnahme von landwirtschaftlichen Versicherungen, wobei den Verhaltensfaktoren besondere Aufmerksamkeit gewidmet wird. Das erste Ziel der Studie besteht darin, einen umfassenden Überblick über die Literatur zu geben, indem der aktuelle Stand der Forschung über landwirtschaftliche Versicherungen als Instrument des Risikomanagements in Entwicklungsländern dargestellt wird. Das zweite Ziel besteht darin, ein theoretisches Modell darüber zu entwickeln und zu testen, wie Risiko- und Ambiguitätspräferenzen sowie Liquiditätsbeschränkungen die Entscheidungen über die Inanspruchnahme einer landwirtschaftlichen Versicherung beeinflussen. Drittens untersucht die Studie den Effekt und die Auswirkungen von Zeitpräferenzen auf Entscheidungen zur Inanspruchnahme von landwirtschaftlichen Versicherungen. Das letzte Ziel besteht darin, die Auswirkungen der rotierenden Spar- und Kreditvereinigung (ROSCA) auf die Investitionen in landwirtschaftliche Betriebsmittel und auf das Wohlergehen der Landwirte zu bewerten, wobei das System des marginalen Behandlungseffektes (MTE) angewandt wird. Zur Messung der Verhaltensfaktoren in den Feldexperimenten werden verschiedene Techniken eingesetzt, darunter Methoden mit und ohne Anreize. Da es in Ghana derzeit keine Versicherungsprogramme für landwirtschaftliche Erzeugnisse gibt, haben wir sowohl Methoden der kontingenten Bewertung als auch diskrete Auswahlexperimente eingesetzt, um die Präferenzen und die Bereitschaft zur Teilnahme an landwirtschaftlichen Versicherungsprogrammen zu untersuchen. Aus der

Durchsicht der umfangreichen Studien geht hervor, dass mangelndes Vertrauen, Liquiditätsbeschränkungen, die unvollständige Abdeckung von Risiken, das mangelnde Verständnis von Versicherungsprodukten und einige Verhaltensfaktoren wie Ambiguität und Zeitpräferenzen die Hauptfaktoren sind, die die Inanspruchnahme von landwirtschaftlichen Versicherungen beeinflussen. Die empirischen Analysen zeigen, dass Risikopräferenzen, Ambiguitätsaversionen und Liquiditätsbeschränkungen die Entscheidung der Landwirte zur Teilnahme an landwirtschaftlichen Versicherungsprogrammen ebenfalls beeinflussen. Darüber hinaus wird die Wahrscheinlichkeit, an Versicherungsprogrammen für landwirtschaftliche Erzeugnisse teilzunehmen, durch Wohlstand, Vertrauen und das Niveau der formalen Bildung positiv beeinflusst. Interessanterweise zeigen die empirischen Ergebnisse aber auch, dass die kurzfristige Messung der Zeitpräferenzen die Nachfrage nach Eigenschaften des landwirtschaftlichen Versicherungsproduktes signifikant verringert, während die langfristige Messung die Nachfrage zu erhöhen scheint. Die Landwirte bevorzugen außerdem Versicherungen mit verzögerten Zahlungen bis hin zur Ernte. Schließlich zeigt die Studie, dass Landwirte mit einer hohen Neigung zur Teilnahme an ROSCAS mehr in landwirtschaftliche Betriebsmittel investieren und im Vergleich zu Nicht-Teilnehmern ein deutlich höheres Betriebseinkommen erzielen. Bei einer hohen Anzahl von Schocks erhöhen die ROSCAS-Teilnehmer außerdem ihre Investitionen in landwirtschaftliche Betriebsmittel und erzielen dadurch ein deutlich höheres Betriebseinkommen. Während Anstrengungen unternommen werden, ein geeigneteres landwirtschaftliches Versicherungsprogramm zu entwickeln, mit dem Ziel einer höheren Inanspruchnahme, sollten informelle Institutionen wie die ROSCAS aus politischer Sicht nicht in den Hintergrund gedrängt werde.

Chapter One

General Introduction

1.0 Introduction

Although the past three decades has seen significant reduction in global poverty, the pace of reduction across sub-Saharan Africa (SSA) has rather been slow (World Bank 2018). A recent World Development Report, for example, cites that a third of the SSA population are still chronically poor, with an additional one-third transitioning in-and-out of poverty (Jorgenson and Siegel 2019). Accelerating poverty reduction in SSA requires deliberate and sustained efforts in identifying niches that hold the greatest potential to lifting the majority from poverty (Soares et al., 2017; FAO 2018).

Agriculture holds an immense potential to reducing poverty in SSA. Indeed, it has been widely documented in the empirical literature that agriculture is significantly more effective at reducing poverty, particularly among the poorest of the poor relative to other sectors of the economy (Christiaensen et al. 2011; de Janvry et al. 2005). Harnessing the enormous potential the agricultural sector possesses in reducing poverty and spurring development requires substantial investments in farm inputs. However, the uncertainties often associated with whether one stands to reap the anticipated benefits of her investments is a major challenge. In the face of the worsening weather and climatic events, these risks and uncertainties are projected to increase (FAO 2013). Hence, efforts at addressing risks and uncertainties remain crucial in the developmental agenda of SSA.

Since farmers are averse to these risks and uncertainties, they usually adopt practices such as crop diversification (Chemura et al. 2020), cultivation of low yielding but resistant crop varieties or reliance on benevolent resources from neighbors in their attempt to minimize their exposure (Takahashi et al. 2018). The limitations of these informal practices in addressing risks

and uncertainties are well-known in the literature (Takahashi et al 2018; Tang et al. 2021), hence researchers introduced agricultural insurance in an attempt to address them. Agricultural insurance is a market mechanism through which farmers transfer their risks of losses to an entity, in exchange for small quantifiable losses to prevent a larger one (Ituirrioz 2009). In contrast to the anticipated uptake, agricultural insurance uptake in developing countries has been abysmal. The co-existence of risk aversion and the low agricultural insurance uptake in developing countries remains a puzzle to researchers till date.

Compared with developed world where the traditional indemnity-based insurance has been operational, attempts to replicate same in developing countries has been extremely difficult because of the ubiquitous small-scale production systems, and the well-known problems of moral hazard[1] and adverse selection[2]. These information asymmetry problems make it prohibitively expensive to operate in the developing world. Hence, the index-based insurance whose payout depends rather on an exogeneous measure which correlates with farmer's losses, but the farmer has no influence on has been introduced (Iturrioz 2009; World Bank 2011). Here, the liability of loss to the farmer is not based on an assessment of her actual losses, but rather, on an objective measure. Weather parameters such as rainfall and temperature, satellite measures of the level of vegetation such as the Normalized Differenced Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), and Area yields are the widely used indices (World Bank 2011)

Following the introduction of the innovative index-based products, basis risk, acknowledged in the literature as the Achilles heel of index insurance, presents a major

[1] Moral hazard occurs when the insurance contracts reduce farmers' incentives to maintain agricultural practices that reduces yield, because of the inability of the insurer to accurately monitor the activities of the farmer (World Bank 2005).

[2] Adverse selection refers to the situation where insurers find it difficult to distinguish farmers based on their risk profiles to inform the payment of appropriate premiums, and as such farmers with high probability of losses tend to participate because of the average price charged by the insurer (Smith and Baquet 1996).

challenge to farmers' uptake decisions (Jensen et al. 2018). Basis risk – defined as the imperfect correlation between farmers' losses and the index that triggers payment would in some circumstances not trigger payments, even though the farmer might have incurred substantial yield losses (Ye et al., 2019). Smith and Watts (2019), for example, report of as low as 27% correlation between rainfall and weather station yields in the Sahel regions of Africa, implying that farmers' losses are less likely to be indemnified. The associated uncertainties, as pointed out by Carter et al. (2017), has behavioral consequences on farmers' decisions to take-up index-based insurance.

According to Budescu and Fischer (2001) the presence of basis risk exposes farmers to making decisions on two stochastic processes. First, the farmer makes decision on whether losses will be incurred, and second, whether the index that triggers payment accurately reflects her losses. These two stochastic decisions create a compound probability that most individuals find difficult to reconcile, making index insurance purchasing decision uncertain. Meanwhile, it is widely documented in the behavioral economic literature that most individuals prefer outcomes with known probabilities (termed risks), as opposed to those with unknown probabilities, also termed ambiguity (Barham et al., 2014; Elabed and Carter 2015; Bryan 2019). The sheer lack of trust in receiving payments in case farmers incur losses further cast doubts on the insurance product (King and Singh 2020). Thus, insurance uptake decision is not solely driven by the highest expected utility conditional on the risk aversion, but also on the level of ambiguity (Barham *et al.* 2014; Bryan 2019), justifying the need to separate the effect of risks from ambiguity.

In the midst of these behavioral factors, many other studies argue that liquidity constraints often limit farmers' ability to translate desires into actual agricultural insurance purchases (Karlan *et al.* 2014; Cole *et al.* 2013). Crop insurance contracts typically require a

farmer to make upfront premium payments, but only receive state-dependent incomes from the insurance purchases on a later date. Traditionally, these initial upfront premium payments occur at the beginning of the cropping season when farmers are usually cash-strapped, and any subsequent receipts occur at harvest times when farmers are less liquidity-constrained. Taking up crop insurance, thus exacerbates the challenge already associated with cyclical nature of farmers' incomes. Indeed, a recent study by Belissa et al., (2019) show that when farmers' liquidity constraints are relaxed, they increase their insurance uptake significantly, suggesting that addressing liquidity constraints is non-trivial in the crop insurance uptake decisions of smallholder farmers.

In the light of these constraints, previous studies that examine the effects of risks and ambiguity on crop insurance decisions have either been empirical (e.g., Belissa et al., 2019), or where the authors incorporate theory (e.g., Elabed and Carter 2015), they have failed to incorporate the role of liquidity constraints, creating a gap that needs further investigations. Developing and empirically testing a theoretical model that incorporates the concept of risks and ambiguity preferences, and liquidity constraints in crop insurance uptake presents a more comprehensive view to inform effective policy measures in addressing them.

In an effort to overcome the widespread liquidity constraints smallholder farmers face in their crop insurance uptake decisions, recent studies recommend deferring insurance premiums until harvest (Casaburi and Willis 2018; Belissa et al., 2019). The empirical evidence from delaying insurance premium payments, so far, has been phenomenal. Casaburi and Willis (2018), for example, randomly assigned a group of sugarcane farmers to either delay their premium payments until harvest or pay at the commencement of the planting season. While only 5% of the farmers who paid upfront took up the insurance product, 72% purchased the

insurance product when the payment was delayed, underscoring the relevance of delaying the premium payments.

However, if farmers exhibit dynamic inconsistencies[3] in their time preferences, this could have serious implications on the sustainability of the insurance scheme. Time preferences which measure the trade-offs among costs and benefits occurring at different times tends to play relevant role in numerous decisions (Duflo et al., 2011; Bauer et al., 2012; Andreoni and Sprenger 2012). If a farmer is so impatient to delay current utility for the future, then such a requires high compensation to motivate a delayed gratification, such a farmer is said to have a high discount rate. On the other hand, if a relatively small compensation is required for the farmer to forego current utility for the future, then the farmer is said to exhibit lower discount rate.

In the insurance literature, lower discount rate is expected to characterize the preferences of a farmer who cares much about her future consumption. A farmer exhibiting lower discount rate is expected to purchase insurance to hedge against her future consumption compared to one with a higher discount rate who rather cares more about the present (Hill et al., 2019). Meanwhile, the classical economic theory also postulates that a risk-averse farmer should demand for insurance to hedge against losses (Clarke 2016). However, if the farmer is risk-averse, and cares less about her future consumption (i.e., high discount rate), this farmer may decide against purchasing crop insurance. This implies that perhaps, the farmer in the latter scenario derives comparatively high utility in consumption expenditure in the current period, relative to the potential smoother future consumption from insurance incomes. Thus, farmers' aversion to risk is a necessity, but time preferences could influence the decision to or not to take

[3] A farmer who exhibits dynamic inconsistent preferences values the present utility highly compared to that from the future. Such a farmer would make choices that make her happy in a moment, and is often described as present-biased.

up crop insurance. It is therefore crucial to gain further insights into how time preferences influence crop insurance uptake decisions.

To measure farmers' behavioral variables, this study combines incentivized and unincentivized methods in our field experiments. The behavioral variables measured include farmers' level of risk aversion, ambiguity aversion, loss aversion, and rate of time preferences. Also, since there are currently no crop insurance programs in Ghana, this study employed both contingent valuation methods and discrete choice experiments to examine the preferences and willingness to participate in the crop insurance programs. In particular, given that the standard index-based insurance product ignores farmers' heterogeneous risks profiles and as such reduce their worth to farmers (Ceballos and Robles 2020; Bucheli et al., 2021), the study considered an ideal area yield insurance (IAYI) product in the choice experimental set-up. The IAYI addresses the significant heterogeneous risk profiles, while not compromising on the lower cost of administration.

With the above contribution to the empirical literature on agricultural insurance, knowledge within the field is increasing tremendously. The body of knowledge generated, however, remains fragmented with a strand of the literature focusing on developing theories to explain various observations underlying agricultural insurance decision-making. Others have largely concentrated on testing hypotheses in empirical analysis. A comprehensive review of the literature of these strands will thus identify niches to further inform research to influence the interesting policy discourse.

Despite the growing body of evidence, there are few studies that provide a systematic review and synthesis of these findings, with the exception of Miranda and Farrin (2012), Carter et al., (2017), Cole and Xiong (2017), Jensen and Barrett (2016), and more recently Kramer et al. (2022). Miranda and Farrin (2012) offer the first extensive review of the theoretical and

empirical literature on index-based agricultural insurance in developing countries. Carter et al. (2017), for example, synthesize the literature focusing particularly on the innovations in the design and implementation of index insurance. Cole and Xiong (2017) on the other hand focused their study on a broader agricultural insurance uptake decision, including showcasing some evidence from the developed countries. In contrast to Carter et al. (2017) who focused on the design and implementation issues, Jensen and Barrett (2016) paid particular attention to the key challenges facing index insurance. Another departure of Jensen and Barrett's study is their concentration on the supply-side challenges, and the broader regulatory environment in the development of agricultural insurance markets. Although these studies provide various insights into the agricultural insurance, they fail to present a comprehensive view incorporating both theory and empirical perspectives to the understanding of a broader audience. Furthermore, the reviews failed to showcase the methodological developments and technological innovations applied in the agricultural insurance sector.

While efforts are underway to improve the uptake of formal agricultural insurance in SSA, it has been recommended in recent times to reconsider some informal institutions given their unique and intriguing manner of mitigating risks to improve welfare. One of these informal institutions, is the rotating savings and credit associations (ROSCAS). ROSCAS are a group of individuals who have voluntarily agreed to contribute, mostly financially, at regular interval towards a pool, which is subsequently allocated on a random basis, through bidding or some other means agreed in advance (Calomiris and Rajaraman 1998).

The recent studies argue that ROSCAS play a crucial role of risk-sharing, and thus offer some form of insurance, *albeit* incomplete (Etang et al., 2011; Calomiris and Rajaraman 1998). However, it remains debatable whether the form of insurance offered is sufficient to stimulate investments in farm inputs (Baland et al., 2019; Klonner 2008). According to Klonner (2008),

ROSCAS tend to mitigate idiosyncratic risks that impacts investment behavior. The role of ROSCAS in stimulating investment under covariate risks, however, has received less attention in the literature.

In general, while there seems to be growing empirical evidence on the drivers of participation in ROSCAS and their impacts on incomes (Rabie 2021; Alhassan et al., 2019; Brunie et al., (2017), there is paucity of evidence on their impacts on farm input use. Understanding the impacts of participation in ROSCAS on investments in farm inputs is crucial given that the low application of farm inputs in SSA has been identified as a major constraint to increasing agricultural productivity that holds the greatest potential to spur the needed economic transformation (Jayne et al., 2019; Adjognon et al., 2017; Sheahan and Barrett, 2017).

In line with the research gaps identified, this thesis seeks to investigate the drivers of the low uptake of crop insurance, as well as examine the impact of an informal institution (ROSCAS) on investment behavior and welfare. Specifically, the study seeks to comprehensively review the literature on agricultural insurance, as a risk management tool in developing countries. The second objective is to investigate how risk and ambiguity preferences, and liquidity constraints influence crop insurance uptake decisions. The third objective is to examine the effects and implications of time preferences on crop insurance uptake decisions. The final objective is to assess the impact of rotating savings and credit association (ROSCA) on investment in farm inputs and welfare. The rest of the thesis is organized as follows: Chapters two to five are the collection of journal articles, based on the specific objectives stated above. Chapter six summarizes, concludes and points out the policy implications of the study.

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Chapter Two

Recent Advances in the Analyses of Demand for Agricultural Insurance in Developing and Emerging Countries

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Abstract

Despite the significant risks and uncertainties that farmers in developing and emerging countries face in their production process, efforts at encouraging them to adopt agricultural insurance to mitigate their production risks have yielded mainly little success. This article reviews the recent literature on the demand for agricultural insurance in developing and emerging countries, by presenting the state of uptake, drivers of the demand for it, and the potential welfare gains from it. Our review reveals that while risk aversion is necessary for the demand for agricultural insurance, liquidity constraints, rates of time preference, basis risk, and trust are equally relevant in explaining the demand for insurance in poor countries. An interesting observation is the increasing number of studies that employ randomized control trials to analyze farmers' uptake of agricultural insurance in developing and emerging countries. Our comprehensive review finds some information gaps in the literature, and we propose some avenues for further research.

Keywords

risk and uncertainty, agricultural insurance, trust, developing and emerging countries

JEL codes: D52, G22, O13

2.1 Introduction

Perhaps the most highly exposed countries to natural and climatic shocks are those in developing and emerging countries (DEMCs), and yet these countries are among the least prepared in effectively managing these risks. A recent Munich RE (Löw 2019) report shows that storms and floods together made up about 88% of the global natural and climatic disaster events in 2018. More than 50% of these natural disasters struck DEMCs in the Asia-Pacific region and Africa, negatively impacting agriculture. These extremely volatile weather and climatic conditions are projected to increase in both intensity and frequency (Bates et al. 2008, FAO 2013), which has called for intense efforts by policymakers and researchers to find innovative means of mitigating their impacts. The high incidence of pests and diseases and highly volatile input and output prices, among other factors, further exacerbate the significant risks agricultural producers face in DEMCs. The welfare consequences of farmers' exposure to these risks without effective mitigation measures are well documented in the economic and policy literature (Rosenzweig & Binswanger 1993, Barnett & Barrett 2008). Dercon (2004), for example, documents how farmers' exposure to rainfall shocks can substantially impact welfare that persists beyond the period the shock was experienced. The continuous exposure to risks, without relevant mitigation measures, have been found to limit farmers' decision making, thereby trapping them perpetually in poverty (Vargas & Angelino 2012).

Farmers in DEMCs have traditionally used several measures to mitigate or cope with risks, including the cultivation of low-yielding but resistant varieties, diversifying their production practices, and mutually sharing risks. Most of these measures may only offer partial reprieve mainly when the risk involved is of high frequency in occurrence but low severity in nature. However, in low-occurring but high-severity conditions with broader coverage, the measures poor farmers use to mitigate risks are often inefficient. When farmers resort to cultivating low-yielding but resistant varieties because of the high-risk exposure, they tend to be less productive,

thereby failing to generate enough income to spur them out of poverty and food insecurity. Insights from an extensive literature review by Alderman & Paxson (1994) illustrate that these informal strategies are likely to have varying impacts on household consumption smoothing. For these reasons, among others, policymakers and researchers have been looking for innovative means of addressing the inherent challenges present in the traditional methods of mitigating and coping with risks. Despite being an important risk-mitigating measure in most developed economies since the eighteenth century (Mahul & Stutley 2010), agricultural insurance was only introduced, sometimes on a pilot basis, in most DEMCs two to three decades ago. Agricultural insurance is a financial mechanism by which risks of losses are transferred from one entity, for example, a farmer to another (insurer), in exchange for a premium or small quantifiable loss to prevent a larger one (Iturrioz 2009).

Despite their increasing significance in the face of extreme weather conditions, agricultural insurance markets remain underdeveloped in most DEMCs owing to known problems of moral hazard and adverse selection. Moral hazard occurs when farmers can influence losses because the insurer cannot accurately monitor their practices. Adverse selection, on the other hand, occurs when farmers with high probabilities of losses tend to be more likely to adopt the insurance program because of the higher expected returns of participating, compared to their counterparts with lower probabilities. An alternative is index-based insurance, where payouts depend on an index that correlates with individual farmers' losses and which farmers have no influence on, has the potential to confront the challenges associated with the traditional indemnity-based insurance (Miranda & Farrin 2012, Karlan et al. 2014). Given its inherent advantages, index-based insurance has received increased attention from researchers and policymakers over the past two decades. However, several pilot and implemented index insurance programs have either completely failed, or uptake has been far below expectations, even with massive government subsidies (Giné et al. 2008, Cole et al. 2013). Giné et al. (2008),

for example, report that only 5% of farmers in India's state of Andhra Pradesh purchased insurance in their experimental study.

Despite the overwhelming evidence of farmers in DEMCs being averse to risks (Dercon & Christiaensen 2011, de Brauw & Eozenou 2014), the low agricultural insurance uptake continues to baffle researchers. Therefore, a growing body of both theoretical and empirical literature seeks to improve our understanding of the reasons for the low demand and the potential welfare gains from its adoption. As argued by some authors (e.g., Giné et al. 2008), farmers' perception of the perceived distribution of benefits from agricultural insurance may be highly uncertain, making the decision of whether or not to purchase insurance similar to the decision to adopt a new technology.

A clear observation on the methodological front is an increasing number of studies using randomized control trials to examine the impact of interventions on farmers' uptake of agricultural insurance in DEMCs. This shift is aimed at ensuring reduced bias and more precise estimates of program counterfactuals (Cai et al. 2015, Hill et al. 2019). In particular, there has been a shift from the use of stated preferences approach in assessing the key determinants of insurance purchasing decisions of farmers (Hill et al. 2013, Tadesse et al. 2017) to exogenously introduced interventions that seek to examine the impact of specific programs on insurance uptake, as well as effects of uptake on farm performance and welfare (Karlan et al. 2014, Cai et al. 2015, Belissa et al. 2019, Hill et al. 2019).

This article aims to comprehensively review the literature on the demand for agricultural insurance and how participation in the insurance programs affect farmers' welfare in DEMCs. We showcase the recent advances in analyzing the uptake of agricultural insurance products in these countries. The rest of the review proceeds as follows: Section 2.2 presents the concept and general overview of the agricultural insurance markets. Section 2.3 outlines theoretical models employed in explaining the demand for agricultural insurance. Section 2.4 reviews some

empirical evidence of the drivers of insurance demand, while section 2.5 presents evidence of the impacts of insurance. Section 2.6 presents the concluding remarks and suggests avenues for further research.

2.2 Concept and overview of Agricultural Insurance Markets

2.2.1 The Concept of Agricultural Insurance

Agriculture is an extremely risky business, with farmers often exposed to a number of market and production risks. Exposure to these risks result in highly volatile incomes that may affect farmers' consumption if the farmer lacks relevant mitigating measures. The sources of agricultural risks include yield losses from adverse weather conditions, including droughts, incidence of pests and diseases, unexpected low output prices, or even unexpected high input prices. Of course, these risks are not unique to DEMCs but also persist in some developed countries. The difference arises from the existence of better mechanisms to address these risks and uncertainties. Some of these measures include efficient irrigation facilities, resistant varieties, and the use of futures markets to hedge against risks and uncertainties. Thus, farmers in developed countries are able to better manage these risks and uncertainties. These mechanisms for managing risks and uncertainties are often nonexistent, or even if they are, they are often beyond the financial capabilities of farmers in DEMCs. Notwithstanding their financial constraints, farmers in these countries have devised measures to address these risks and uncertainties. However, these measures frequently prove to be inadequate if the risks affect a large number of people within the same geographic enclave at the same time.

Agricultural insurance is one mechanism to manage risks in agriculture by safeguarding farmers' income losses under adverse conditions beyond their control. It provides the financial mechanism for a farmer to either transfer the whole or part of their losses to an entity (insurance firm), through the payment of a small quantifiable amount in exchange for a larger potential loss (Iturrioz 2009). Based on the level at which damages are assessed and insured, insurance

can be broadly classified as indemnity-based or index-based. While claim payments are determined based on actual losses the policyholder incurs in indemnity-based agricultural insurance, the index-based agricultural insurance is based on an index—a measure highly correlated with losses that cannot be influenced by the policyholder. Although there still exist some indemnity-based agricultural insurance programs in some DEMCs, most of the insurance programs implemented for the past few decades have mainly focused on index-based schemes, because of reasons of reduced administrative costs, moral hazard, and adverse selection challenges. In the next section, we discuss indemnity-based insurance.

2.2.2 Indemnity-based insurance

This type of insurance is a financial mechanism that exists between a farmer and an insurance firm, such that the policy covers farmers' actual or potential losses at the farm level, with payouts accordingly made at the level of losses incurred. Indemnity-based insurance can be either single peril or multi-peril, depending on the number of losses the policy covers. Single or named-peril indemnity covers damages for an individual or specifically named perils such as fire, hail, pests, and diseases. When such losses occur, the insurer assesses the extent of the damage at the insured unit, and payments are made according to the terms of the policy. Multi-peril, on the other hand, provides insurance coverage for losses caused by virtually any peril other than that specifically excluded from the policy. Indemnity-based insurance is characteristically expensive to operate because of the high operational costs in assessing losses at the individual farm levels. They are, therefore, much more prevalent in regions with robust welfare systems and more mature agricultural markets.[4] A typical example is the government-

[4]Indemnity-based insurance makes up about 62% of all agricultural insurance underwritten in Latin America and about 70% in Eastern Europe and Central Asia. It only constitutes about 24% in Africa.

subsidized multi-peril crop insurance program in China, in which the state (including province and county) subsidizes up to 80% of the insurance premium (Krychevska et al. 2017).

A related issue with operating indemnity insurance is the insurer's inability to accurately monitor the production activities of the insured to reduce opportunistic behavior. When the insurer is unable to accurately monitor the activities of the farmer, the farmer may be incentivized to alter her production activities to influence losses. A more significant challenge is the tendency for farmers with a higher probability of incurring losses participating in the program, in which case, the insurer increases the cost of the product because the company has no accurate information to price discriminate between high-risk and low-risk farmers. This, in turn, crowds out farmers with lower probability of incurring losses, making the insurance unsustainable. These operational challenges increase the need for an alternative insurance product, index-based insurance.

2.2.3 Index-based insurance

In index-based insurance, on the other hand, payment of liability and amount payable are based on the measured value of an objective and independent index. The liability is not based on proof of a specified loss or the assessment of the actual losses, hence making them less costly to administer. The main advantage of index insurance resides in its ability to substantially reduce the incidence of moral hazards, recognized in the insurance literature as one of the major causes of underdevelopment of the insurance market. Weather and area-yield index insurance constitute the two main index insurance types currently on the insurance market. However, there have been significant increase in experimental index-based livestock insurance (IBLI) across some parts of Africa. While measures of weather parameters, such as the amount of rainfall within a specified period, are used as indices for weather index insurance, a percentage of average yield in a specified geographic area is used for an area yield. Satellite measures of the normalized difference vegetation index (NDVI) also serve an essential role as an index for

both crop and livestock index insurance. These measures of indices continue to evolve with better indices under development to improve risk measurements (Flatnes & Carter 2015, Guan et al. 2016).

Despite its appeal in addressing some of the pertinent challenges associated with an indemnity-based insurance, the index-based program may be fraught with challenges. Indices that form the basis for indemnifying losses for the index-based programs are often more appropriate for homogeneous settings. In reality, however, it is often either too expensive to collect data to design a product for such homogeneous settings or it may be totally infeasible to undertake particularly in developing countries' context (Smith & Watts 2019). For these reasons, among others, there may be a weak correlation between these indices and farm level losses. Smith & Watts (2019), for example, document studies that report as low as a 27% correlation between rainfall and weather station yields in the Sahel regions of Africa. This may result in farmers incurring losses, but the index failing to trigger payments to indemnify these losses. Under this condition, termed downside basis risk, farmers are much worse off, because in addition to losses incurred on their farms without receiving indemnities, costs are incurred on premium payments. On the other hand, given the potential disparity between indemnity activating indices and farm level losses, the index may trigger payment even though farmers may not have incurred losses; this is termed upside basis risk. Of course, farmers are better off under this condition, but the insurer experiences high loss ratios and may undergo financial distress, putting the sustainability of the insurance program into question.

2.3 The Agricultural Insurance Market Overview

The global agricultural insurance markets have increased considerably over the past decades, mainly because of the exponential growth in premium contributions from some DEMCs, particularly from China and India. For example, the agricultural premium for China grew by 342% from US$1.84 billion in 2006 to US$6.3 billion in 2016, compared to the global growth

of 191% over the same period (excluding China). With this strong growth, China's share of the global agricultural insurance premium increased from 1% to 23% over the same period. This trajectory, as shown in Figure 2.1, is projected to continue, as the value of agricultural products in China and other DEMCs continues to grow (Swiss Re 2013, Krychevska et al. 2017).

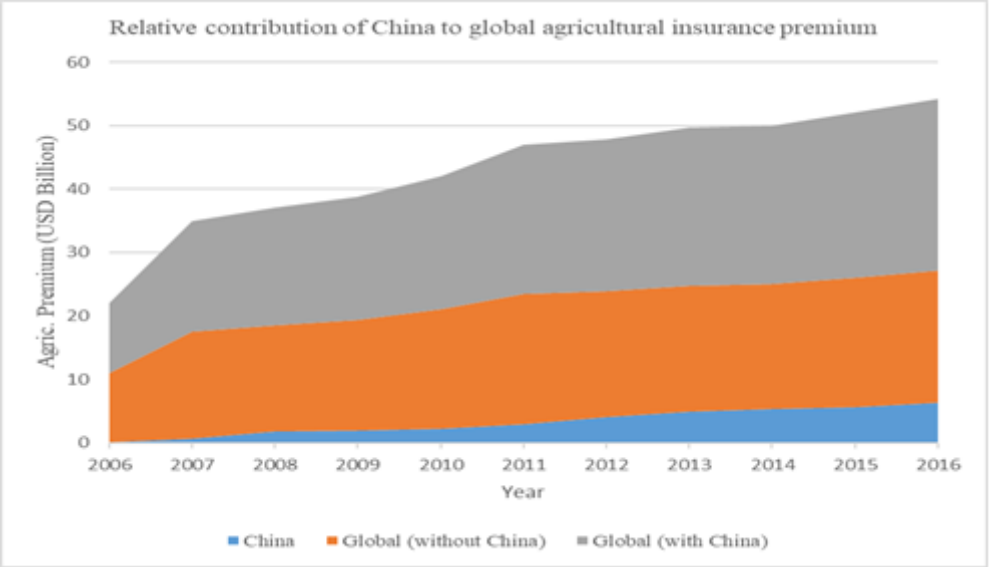

Figure 2. 1: Relative contribution of China to global insurance premium. The growth of the Chinese agricultural insurance market in relation to the global agricultural insurance premium growth. Data from Mahul & Stutley (2010), Swiss Re (2013), Löw (2017), and Krychevska et al. (2017).

There have been rapid developments in the agricultural insurance markets in Latin America and the Caribbean. For the past two decades, agricultural insurance premiums have doubled every five years, reaching $1.6 billion in 2015 (Swiss Re 2016). This exponential growth has been primarily driven by Brazil, Mexico, and Argentina. In terms of volume, about 61% of the insurance premiums were written in Brazil, while Mexico and Argentina contributed about 30%. The rest were written in countries such as Peru, Guatemala, and Cuba (Swiss Re 2016). The insurance market operations span complete government control through private-public partnerships to commercial operation. In the Caribbean, for example, agricultural insurance has featured prominently in the government and development partners' agenda in mitigating the

impacts of climate in the region. Climate Risk Adaptation and Insurance in the Caribbean is an innovative two-phase project implemented in several regional countries to mitigate climate-induced disasters in the region (World Bank 2010, Swiss Re 2016).

With the exception of South Africa, where agricultural insurance has been in existence since the 1970s, most countries on the African continent have only been introduced to the program, mostly at pilot levels, only within the last two decades (Hess & Hazell 2016, Miranda & Mulangu 2016). Between 2011 and 2016 for example, Sahel Crop Insurance, a weather-based insurance, was piloted across a number of West African countries in the Sahel region owing to the worsening incidence of droughts. The World Bank and other international development agencies spear headed these pilot projects across countries such as Senegal, Mali, and Burkina-Faso. These programs have primarily focused on corn, as a food security crop, and cotton and peanuts as commercial crops. In addition to instituting and piloting index insurance for crops, that for livestock has also been piloted in these regions (Miranda & Mulangu 2016). In particular, the IBLI was piloted in northern Kenya in 2010 and then subsequently extended to Ethiopia. A year after introducing the IBLI, uptake fell considerably by about 70% from 1,979 subscribers in 2010 to 599 subscribers in 2011 (Miranda & Mulangu 2016). Despite the initial disappointing results, researchers and policymakers expect improved uptake through the continuous efforts to improve program designs and other policy interventions (Miranda & Mulangu 2016).

2.4 Emerging Trends in Agricultural Insurance: Information and Communication Technologies

With recent advances in information and communication technologies (ICT), there has been an increased application of ICT to address some of the challenges inherent in the agricultural insurance market. In particular, delivering insurance to sparsely populated areas of farming households in developing countries significantly increases the operational costs. Hence, there

is an emerging trend to apply ICT to decrease these costs. Although the African continent continues to be a beneficiary of these modern technologies in the agricultural insurance markets, most of the revolutions are taking place in Asia. We briefly itemize some of the critical trends of the implementation of ICTs in agricultural insurance.

- Ceballos et al. (2019) document the feasibility of incorporating smartphone pictures into index-based insurance to reduce the incidence of basis risk in India. Leveraging the increasing number of smartphone users among farmers, the authors show that farmers could take pictures of their farms at various stages of maturity for onward assessment. The authors find a significant reduction in downside basis risk for picture-based insurance compared to weather index-based insurance and area-yield insurance.
- Although the field of machine learning is nascent to the area of agricultural insurance, there are emerging trends for the application of deep learning and artificial intelligence to better predict weather risks and to inform better agricultural insurance administration.
- Regarding the application of ICT in the livestock insurance sector, researchers are piloting the possibility of using artificial intelligence to identify farm animals to improve performance of the livestock insurance market (Kumar et al. 2016).

2.5 Theoretical Models

Although the expected utility theory (EUT) formally developed by von Neumann & Morgenstern (1944) continues to be the standard for explaining decisions under uncertainties, there have been new developments, apparently because of some fundamental inconsistencies in the assumptions underlying the EUT to explain agricultural insurance demand. Researchers have for some time resorted to using behavioral models to explain some of these apparent inconsistencies in the observed demand for agricultural insurance. We review these evolving

theories on agricultural insurance literature in this section. We begin with the two dominant theories by first summarizing the literature on the expected utility and then the prospect theory. Other behavioral models are also presented.

The EUT postulates that people maximize their expected utility in their decisions to purchase or not purchase insurance. This decision is driven by the curvature of their utility function, which in turn is determined by the level of risk aversion. Basically, if consuming more of a good result in correspondingly lower additional utility relative to the previously consumed good, then the marginal utility is said to decrease, resulting in a concave utility function. Individuals who exhibit this kind of utility function are said to be risk averse. On the other hand, when marginal utility increases over wealth, a convex utility function is obtained, and individuals displaying his utility function are described as risk seekers. However, when the marginal utility from an additional unit consumed remains constant, the utility exhibits a linear function, and such persons are said to be risk neutral. Due to the concavity of the utility function, the risk-averse individuals always prefer outcomes that are certainly known to uncertain outcomes. Thus, such risk-averse individuals are willing to pay a positive price to avoid such risks. In fact, this willingness to pay behavior is the underlying reason for the development of the insurance market. A brief description of this theory is presented in Figure 2.2*a*,*b*.

To illustrate how risk aversion affects insurance demand, let us assume a farmer has two plots of land, A and B, on which to farm. Plot A is less fertile but without incidence of locust pest attacks. Plot B is more fertile but susceptible to locust pest attacks. When the farmer cultivates plot A, she is certain to obtain 20 tonnes, and with a price of $10 per tonne, this implies the farmer receives $200. Cultivating Plot B, in a different location, yields 40 tonnes in the absence of locusts, but the farmer obtains 0 tonnes with locust attack. With a 50% chance

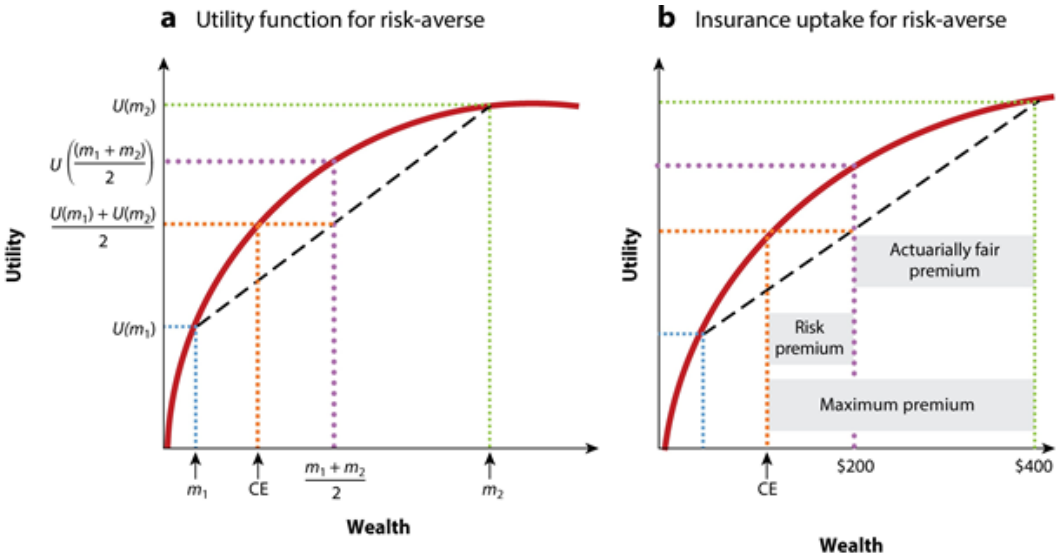

Figure 2.2: An illustration of expected utility theory explanation for demand for insurance by the risk-averse individual. If we assume a 50% probability, the expected value of m_1 and m_2 is $(m_1+m_2)/2$ on the horizontal line (fig. 2a). The **utility of the expected value** of wealth, is strictly greater than the **expectation of utilities** $U(m_1)$ and $U(m_2)$, because of concavity of the utility function, i.e. $U[(m_1+m_2)/2] > \frac{U(m_1)+U(m_2)}{2}$. To obtain the utility of the expected value of wealth, the risk-averse will be willing to pay a positive price difference between her expected value of wealth and her certainty equivalent (CE). Tracing to panel *b* the maximum premium is the sum of the risk premium and the actuarially fair price. Generally, the more risk averse an individual, the more concave the utility function and the larger the risk premium, and by extension, the higher the maximum premium she will be willing to pay to be insured. Adapted with permission from Patt *et al*., (2009).

of locust attack, the farmer receives $400 in the absence of the pest attack, or $0 when there is an attack. On average, the farmer is expected to incur losses of $200 for cultivating plot B. Given that cultivating plot B is associated with uncertainties, and an insurer is willing to pay $400 in case of crop failure, a risk-averse farmer will be willing to pay up to the difference between $400 and her certainty equivalence[5] in premiums to hedge against this potential crop failure (see Figure 2.2b). A more risk-averse farmer will have a more concave curvature in the utility function, implying a higher difference between the actuarially fair premium and the

[5]The concept of certainty equivalence refers to an amount of money (income) that is equivalent in an individual's mind (in utility terms) to a given uncertain situation. It is the subjective value one attaches to a certain outcome relative to a given uncertain outcome.

certainty equivalent; therefore, the maximum willingness to pay for the insurance will be higher. Thus, higher risk aversion is expected to lead to higher demand for insurance.

The rational theory of demand for insurance explaining that risk aversion is monotonously increasing in demand for insurance is generally consistent with indemnity-based insurance. However, recent evidence on index insurance in some DEMCs shows significant inconsistencies. Numerous studies on index insurance demand show evidence that contradicts the rational demand for insurance (e.g., Giné et al. 2008, Cole et al. 2013, Hill et al. 2016). Building upon the study of Doherty & Schlesinger (1990), Clarke (2016) shows that a more specific contract nonperformance (i.e., basis risks) creates additional risks. Hence, the disutility from this additional risk dominates for individuals with higher risk aversion, resulting in risk aversion decreasing the demand for index insurance. As shown in Figure 2.2, a risk-averse individual will always demand insurance coverage by being willing to pay a positive price to avoid risks. However, recent studies show that demand for index-based insurance by risk-averse individuals initially increases with risk aversion up to a point and starts declining thereafter (Clarke 2016, Hill et al. 2019).

Among the nonexpected utility theories, prospect theory is considered the most convincing in emphasizing three main factors to explain the inconsistencies inherent in the expected utility theory: loss aversion, reference dependence, and probability weighting. At the core of prospect theory is the argument that for the same amount, the disutility from losses is higher than the utility of gains. Thus, contrary to the EUT that apportions equal weights to disutility from losses and utility of gains, the prospect theory points out that this cannot be the situation. From a series of experiments, Kahneman & Tversky (1979) concluded that to the extent that the disutility from avoiding losses is higher than the utility from gaining the same amount, individuals are averse to losses. It is worth mentioning that in prospect theory, relatively higher aversion to losses makes insurance valuable, as compared to the concavity of the utility function in EUT,

because of the higher associated disutility from losses. A related issue, probability weighting, is the tendency for individuals to distort objective probabilities by overweighting worst-case scenarios. This is quite intuitive, as given the increasing incidence of extreme weather conditions, the tendency for individuals to overweight events that hitherto were quite rare is now common. Prospect theory incorporates this tendency of overweighting rare events in contrast to the EUT. Finally, in their production processes, it is often common for farmers to have some reference points for valuation. Most farmers produce with target prices for their output in mind. The utility from gains beyond this reference is comparatively lower than the disutility from obtaining less than this reference point. In some developed countries, for example, this occurs through the farmer's target on the futures markets (Kim et al. 2010).

Individuals' aversion to uncertainties on the distribution of outcomes has been attributed to the low demand for agricultural insurance. Following Ellsberg's (1961) distinction between uncertainties with known and unknown probabilities, economists have demonstrated the relevance of the distribution of uncertain outcomes on agricultural insurance demand. Although they appear similar, ambiguity aversion is different from risk aversion: while an individual who is ambiguity averse always prefers an uncertain outcome whose probability is known, a risk-averse individual tends to dislike uncertainties outright. The mechanism through which ambiguity aversion affects insurance demand is better represented in index insurance, where payouts are based on the outcome of an exogenous factor. To the extent that this exogenous factor does not perfectly correlate with observed outcomes at the farmer level, the distribution of farmers' losses will thus likely be different from that of the indemnity-triggering index. It is, therefore, often difficult for farmers to perfectly predict the result of this compound probability that arises from these two distributions (Elabed & Carter 2015). In a recent empirical study on farmers in three African countries, Bryan (2019) demonstrates that ambiguity aversion matters in crop insurance adoption decisions.

The role of credit constraints on the demand for agricultural insurance has long been of significant interest to researchers, given its multidimensional potential impact on insurance demand. On the one hand, the liquidity-constrained individuals are expected to value insurance to stabilize their incomes, given the adversarial effects of fluctuating incomes on consumption. On the other hand, these farmers are unable to convert potential desires into purchases, not only because of issues of costs, but also the time farmers are expected to make these purchases. Because farmers often have to pay for insurance up front at the commencement of the farming season, when they are often cash strapped, they may be less willing to pay for insurance. Although insurance purchasing decisions aim at reducing risks, the insurance product, and index-based programs in particular, come with additional risks because farmers are not entirely certain that indemnities will be paid. When farmers are liquidity constrained, they often tend to pursue less-risky investments, thereby forgoing purchasing insurance due to the uncertainties of receiving payments (Rampini & Viswanathan 2010). These mechanisms through which liquidity constraints influence agricultural insurance have been extensively explored in the empirical literature. Some findings from these empirical studies will be discussed later.

2.5.1 Basis Risk and Insurance (Index-based) Demand

The widespread challenges of informational gaps, in particular, adverse selection and moral hazard that characterize the indemnity-based insurance, necessitated the design of an alternative program aimed at minimizing these challenges, led to index-based insurance. The index-based insurance where payouts depend on an exogenous and publicly observable index (measure) has mostly been successful in addressing the challenges of moral hazard and adverse selection. However, given the potential for farmers to incur losses, and yet the index's failure to trigger payments, farmers' demand for index insurance has been disappointingly low. This probably might have informed Binswanger-Mkhize's (2012) cautious note of not to overhype index insurance and that farmers must be studied on a case-by-case basis. Over the past decades, there

has been increasing attention in the theoretical literature to describe and explain the mechanisms through which basis risk affects insurance uptake in developing and emerging economies (e.g., Clarke 2016, Jensen et al. 2016).

To motivate the discussions, we briefly present some theoretical implications of basis risk on insurance uptake. Clarke (2016) demonstrates in his theoretical paper that the presence of basis risk can worsen farmers' income through premium payments to the insurer in an adversarial state of nature and yet not receive indemnities. Thus, in a bad state of nature (i.e., yield losses), farmers who purchase insurance, but find themselves in a situation where the index fails to trigger payouts, are much worse-off compared to counterparts who did not purchase; the same applies to those farmers had they not purchased insurance. Given the uncertainty associated with the likelihood of receiving payouts, although cost would have been incurred, the farmers may be reluctant to purchase the insurance product. Clarke further points out that the lower demand for index insurance coverage, even among risk-averse farmers, could be partly explained by basis risk. For this reason, index-based insurance is often less valued by farmers, resulting in low demand.

2.5.2 Social Networks and Insurance Demand

In most rural settings, families often interact. These social interactions have been shown to have consequences on economic outcomes. Understanding the nature and mechanisms underlying the role of social networks on agricultural insurance demand is of significant relevance, given the prevailing weak formal institutions in promoting and delivering alternative means of insurance against shocks. The economic literature has identified two main mechanisms through which social networks influence agricultural insurance demand: the risk-sharing and the information-sharing networks.

The literature on measuring and modeling the impact of social networks on demand for agricultural insurance has primarily focused on either the nonstrategic or strategic roles. While

the nonstrategic role of social networks mainly focuses on network structures as conduits for information transmission, the strategic mechanism entails how farmers share resources in times of shocks in addition to the network structure. This has been found to play a significant role in the demand for agricultural insurance in most DEMCs, where social networks tend to serve an essential ex post risk-coping role in the absence of a formal insurance system. In this section, we address some emerging issues regarding the role of these two social network mechanisms in agricultural insurance demand.

2.5.3 Information diffusion role of social networks

Cai et al. (2015) argue that financial decisions—in particular, decisions to purchase insurance—are quite complex, and frequently, potential buyers of these products either learn about the products through their friends or are sometimes influenced by their friends' choices. However, an important observation was made that friends' decisions to purchase did not have any significant impact on one's purchasing decisions. Instead, when these same individuals were informed of the decisions of their peers, it significantly influenced their own insurance uptake. The authors therefore concluded that the primary mechanism through which social networks affect insurance uptake is through social learning and not necessarily a friend's purchasing decision. Using a randomized experimental design approach in Indian villages, Banerjee et al. (2013) show that the most important channel for individuals to participate in microfinance programs was acquiring information from friends. This indicates that social networks are quite relevant in influencing participation through information sharing. These studies indicate the knowledge acquisition mechanism of insurance purchases, rather than imitating friends' actions.

2.5.4 The risk-sharing role of networks

In the absence of formal insurance, people may rely on informal risk-sharing mechanisms in coping with risks. It is often common to observe people in rural areas helping one another

whenever disastrous events occur. However, it has been argued that these risk-sharing networks often occur at a limited level among family and friends, without extending to all inhabitants in the entire village (Fafchamps & Gubert 2007), thereby rendering it less effective in achieving full insurance. Even in situations where risk-sharing exists in the village, they are often inefficient in achieving the desired impact because of ineffective enforcement and limited commitment (Barr & Genicot 2008, Attanasio & Pavoni 2011).

It has been largely debated in the economic literature as to whether the informal risk-sharing networks play a substituting or complementary role to formal insurance. Fafchamps (1992), for example, argues that risk-sharing networks, on the one hand, can serve as a substitute and a complement to formal insurance on the other. He argues that as a complement, informal risk-sharing networks are able to provide some coverage to the residual risk because of the imperfect correlation between farmers' observed losses and the indemnity-activating indices for index-based insurance. However, the same informal risk-sharing may play a substituting role to the formal insurance, if leaving the group decreases the risk-pooling ability of the group. Dercon et al. (2014) offer a theoretical explanation for only the former, arguing that informal risk-sharing networks complement formal insurance by mitigating the inherent basis risks associated with index-based insurance.

Takahashi et al. (2018) argue that in index-based insurance, for example, where the presence of basis risk has been observed to significantly decrease the demand for formal insurance, informal risk-sharing networks and formal insurance reinforce each other. First, they argue that given that index insurance may fail to trigger payment even though a farmer incurs losses, an informal risk-sharing group can fill this gap. On how formal insurance can also complement risk sharing, they argue that these groups are often able to mitigate the effects of idiosyncratic risks. However, these risk-sharing groups are often ineffective in mitigating covariate shocks

because a larger number of households are affected at the same time. Hence, formal index insurance could play the important role in reducing this covariate risk.

In a recent study, Berg et al. (2017) contribute to the debate on the relationship between risk sharing and formal insurance. In particular, they demonstrate how risk-sharing networks decrease the demand for indemnity insurance but increase the demand for index-based insurance. In an artefactual field experiment in Ethiopia, the authors empirically test the role of risk sharing on both indemnity-based and index-based insurance. Their findings indicate that risk sharing decreases units of indemnity insurance purchases by 27%, while increasing the uptake of index-based insurance by 130%. These findings further stress the relevance of designing an insurance product to minimize residual risks inherent in index-based insurance as much as possible to improve the welfare of poor farmers in developing countries.

2.6 Empirical evidence on the drivers of Agricultural Insurance demand

Several studies have analyzed the drivers of farmers' participation in agricultural insurance programs in developing and emerging economies. The various methodologies employed in these empirical analyses range from observational through quasi-experimental to experimental. However, given the recent increase in evidence from experimental studies, the sections below focus on these examples.

2.6.1 Credit or Liquidity Constraints

A growing body of literature shows the relevance of the timing when insurance products are offered to farmers on their uptake. A characteristic feature of most farmers in developing countries is the possession of cash at harvest from sales of farm products, which tends to decrease as the planting season approaches because of purchases of farm inputs. To the extent that many farmers tend to be liquidity constrained during the planting season, an up-front payment for agricultural insurance is often a challenge to these poor farmers. Several studies

have analyzed these insurance up-front payment problems and explored the potential of offering insurance with delayed payments that take place during the harvest period.

In a recent study, Casaburi & Willis (2018) employ a randomized control trial to examine how delayed insurance programs to Kenyan sugarcane farmers interlinked with contract farming impacted insurance uptake. They hypothesize that selling insurance products to these farmers during harvest will increase uptake because they are less liquidity constrained after receiving incomes from their harvests. Consistent with their hypothesis, they find that only 5% of farmers who had to pay the insurance premium upfront opted for the insurance product, while 72% of the farmers who were offered the insurance at the harvest period took up the product. Even with 30% discount provided to farmers who paid up front, the insurance uptake only increased to 6%. In a more recent study, Belissa et al. (2019) also use a randomized control trial to test a similar hypothesis. They argue that, given the relatively low amount of contract farming in most developing countries, offering similar products devoid of contract farming was more externally valid. After offering insurance products with delayed payment until harvest, they observe a significant increase in uptake of the product. Specifically, uptake increased by threefold from 8% to 24% with insurance premium payment delays. At a disaggregated level, they observe higher uptake among farmers who were liquidity constrained, though this difference was not statistically significant.

Even though we set out to review studies that employed experimental approaches, we nevertheless point out one particular study that sought to test poor farmers' preferences for an alternative means of paying for insurance programs other than using cash. Using the stated preference approach in rural Ethiopia, Tadesse et al. (2017) assess farmers' willingness to pay for weather insurance with cash alone, labor (work) alone, or a combination. One of their main findings is that farmers were willing to offer their labor for the insurance program at wages lower than the going rates on public work programs. They conclude that these farmers were

severely cash constrained and more willing to pay with their labor, which they have in abundance compared to cash.

2.6.2 Rate of Time Preferences

There is increasingly abundant literature that explores the role of how farmers discount future benefits on insurance uptake. Despite the primary purpose of insurance in reducing risks through the transfer of incomes from high-income states to low-income states, some researchers have found evidence of the investment appeal of insurance (Connor 1996). In addition to the nature of insurance that requires an up-front payment for a premium, this has necessitated the increased attention on the role of farmers' discounting of future benefits on agricultural insurance adoption in most developing countries. In an experimental study in Bangladesh, Hill et al. (2019) randomly assigned villages to discounts and rebates to examine how farmers' time preferences affect their demand for agricultural insurance. Their empirical results reveal that discounts tend to stimulate insurance demand more than rebates. Their findings give further credence to the notion that farmers in DEMCs prefer current benefits compared to future ones.

2.6.3 Trust

When farmers have doubts about either the insurance product design itself or the likelihood of receiving payment when they incur losses, they tend to be hesitant in taking up insurance products. These attitudes often originate from the weaker formal institutions involved in the enforcement of contracts in most DEMCs. Literature on the impacts of trust on insurance uptake has mostly been centered on three main themes: the product itself, institutions responsible for the management of the insurance product, and the degree of interpersonal trust. These dimensions of farmers' trust behavior continue to attract the attention of empirical economists, given the relevant role trust plays in insurance demand.

Most studies attribute the distrust of the insurance product itself to the farmers' misunderstanding of the insurance product. Given the generally low level of formal education of rural individuals in developing countries, most farmers tend to have minimal knowledge of the concept of insurance. If not properly understood, these farmers often consider insurance products to be similar to investment options, which, when they fail to receive payouts, generally lead to distrusting behavior. Distrust emanating from the insurance product has been found to diminish and subsequently increase uptake when farmers witness payouts. In Ghana, Karlan et al. (2014) used a randomized control trial and find that the demand for insurance increases when farmers observe payouts for members in their social networks or when they experience payment from the insurance. As already indicated, in the absence of formal institutions to enforce contracts in most developing countries, trusted informal institutions tend to fill the void. Following a randomized control trial in Ethiopia, Belissa et al. (2019) report that although index insurance uptake was only 8% in the standard marketing channel, when it was marketed through an informal institution called *Iddir*, whose leaders are generally well trusted, uptake doubled to 15%. This finding supports the importance of trust in the institutions involved in scaling up the uptake of insurance products.

2.6.4 Basis Risk

As discussed in the theoretical review in section 2.5.1, basis risk presents a major challenge to farmers in their adoption decisions of index-based insurance. It appears to represent one of the most significant risks to the development of index-based insurance markets. In a comparative study of the cost-effectiveness of indemnity-based and index-based insurance in China, Ye et al. (2019) find that the positive price advantage from index-based insurance may not be sufficiently large to offset the costs associated with its basis risk. These findings further highlight the reason underpinning the continuous and sustained interests in understanding and minimizing basis risks. In an earlier innovative study to test the impact of basis risks on weather

index insurance, Mobarak & Rosenzweig (2013) randomize weather station placements in Indian villages. This study was among the first to empirically test the impact of basis risk on index-based insurance demand. Their findings show that basis risk significantly decreases the demand for weather index insurance. In a panel study on the Kenyan IBLI program, Jensen et al. (2018) report a significant decrease in both the uptake and level of coverage of the insurance program. Note that while other studies have often relied on proxies as their measure of basis risk, Jensen et al. (2018) use actual data from farm purchases.

Given the important role of basis risk on index-based insurance demand, some researchers have proposed innovative insurance products that aim at addressing the problem. For example, Elabed et al.'s (2013) study on cotton farmers in Mali recommends a multilevel yield index, one at the village level, and the other at the regional level to increase demand. Other studies have proposed and implemented a hybrid index to minimize basis risks. The study by Hill et al. (2019) on Bangladesh implements index-based insurance that is triggered by both the area yield and the rainfall index. This insurance program is expected to decrease both upside and downside basis risk.

By exploring how to minimize basis risk from the product design perspective, Xiao & Yao (2019) investigate three index-based insurance products triggered by two indices (i.e., weather and area yield) under different scenarios. The first is the superimposition type that separately incorporates indemnity payments from the weather index and the area-yield index at the same time. With this, if either the weather or area-yield index is triggered, the farmer receives payments. In supplement type, payments are made only when the weather index fails to trigger payments, but farmers still incur losses to such a point that the area-yield index triggers payment. For this, as the name suggests, the area-yield index supplements the weather index. Finally, there is the rebate type in which premiums that farmers paid are returned to them when the weather index fails to trigger payments, but the area-yield index triggers payments because

of poor yields. This can be a common scenario when the total amount of rain required for a given crop is enough but is poorly distributed. Xiao and Yao's simulations and empirical findings show improved performance of the supplementary type of insurance. Findings from this study provide relevant information to inform the design of indices for future index-based insurance.

2.7 Evidence of the impacts of Agricultural Insurance

To the extent that agricultural insurance has been identified as one primary way of reducing the risks and uncertainties faced by farmers in DEMCs, many studies have also analyzed the determinants of uptake and welfare impacts of these insurance products. These studies have primarily been undertaken with diverse approaches, including the use of experimental and observational data. In this section, we discuss some of the recent findings from studies that have examined the impacts of agricultural insurance on well-being indicators. We first briefly review studies that used simulations and then delve deeper into those that used either observational or experimental approaches.

In the absence of rigorous experimental methods of assessing the impacts of insurance on some welfare measures, researchers have long relied on either simulations or observational data. Carter et al. (2007) for example, applied the simulation method to show that insurance provision significantly improves farmers' welfare as well as their access to and supply of loans and repayments in Peru.

2.7.1 Ex Ante Impacts of Investment Decisions

Karlan et al. (2014) investigate the investment response of relaxing the binding uninsured risks and liquidity constraints of maize farmers in northern Ghana. After randomly assigning farmers to either cash grants, index insurance, or both, they observed that investments in chemical fertilizers significantly increased for farmers who purchased insurance in a similar proportion to those who received cash grants. Spending on fertilizer is a risky investment, given that in a

bad state of nature, particularly the lack of rain, farmers are not likely to reap the benefits from the fertilizer applied. The authors conclude that uninsured risks present a significant drawback to farmers' investments and that when relaxed through the purchase of insurance, farmers are able to find the needed resources to achieve this objective.

Using a natural experimental approach, Cai (2016) demonstrates that Chinese farmers can expand land allocated for the production of tobacco by about 16% after purchasing an indemnity-based insurance product from the government. Similarly, an earlier study by Cai et al. (2015), also using randomized experiments in Southern China, showed that investments in sows increased significantly after the purchase of insurance. Recognizing the hinderances of uninsured risks, the authors conclude that insurance can play an equally important role as microfinance in increasing the production of risky sows. A comparative study on cash transfers and index-based insurance in Kenya by Jensen et al. (2017) also reveals that investments in livestock increase significantly after farmers purchase livestock insurance. This was mainly through increased expenses on veterinary services that are expected to increase livestock productivity because of improved health.

Using a natural experimental design, Freudenreich & Mußhof (2018) also contribute evidence of the ex-ante impacts of insurance by analyzing how insurance purchase influences the adoption of improved varieties by Mexican farmers. Their findings show that purchasing insurance significantly affects the adoption of improved maize varieties. However, in an earlier study, Brick & Visser (2015) find no evidence of adoption of improved varieties after farmers purchased partial insurance in South Africa. Despite this limited evidence to the contrary, it is apparent that when risks are adequately addressed through the provision of insurance, farmers can increase investments in risky production practices, which is expected to generate higher returns and improvement in welfare.

2.8.2 Ex Post Impacts of Insurance

Economists have often argued that when poor farmers adopt agricultural insurance, it has the potential to reduce the fluctuations often associated with their incomes and consumption because of their continuous exposure to uninsured risks. Indeed, most studies have shown the negative repercussions when farmers have minimal mitigations to risks (Rosenzweig & Binswanger 1993, Dercon 2004, Barnett & Barrett 2008). However, what is lacking is convincing evidence from DEMCs showing that purchasing agricultural insurance has income and consumption smoothing effects. As Cole & Xiong (2017) rightly point out, answering this question requires first establishing that risks induce income fluctuations in the absence of insurance. Second, farmers should either partially or fully be unable to mitigate these income fluctuations to smooth their consumption. Finally, payouts from the coverage should be sufficiently large to cover the losses farmers incur from their exposure to these risks.

In their recent study on Ethiopian livestock owners, Gebrekidan et al. (2019) demonstrate that the purchase of index-based insurance contributes to a decline in distress sale of livestock. This is extremely important because, in times of extreme weather shocks, farmers without any insurance product or other means of coping with this shock tend to sell their livestock. With a significantly large number of livestock owners willing to sell, prices will naturally decrease because of the increased supply. This action presents double jeopardy to owners of these livestock. On one hand, they tend to lose their productive assets, which makes it difficult for them to cope with future shocks; on the other hand, doing so at a lower prevailing price will generate inadequate income for them to fully cope with the current shocks.

2.8 Some Topical Policy Issues

There is an ongoing policy discussion on where to situate agricultural insurance towards the achievement of broader developmental goals in DEMCs. For example, should agricultural insurance be subsidized? What role should agricultural insurance play in achieving broader

welfare policy objectives? We briefly shed light on how these questions have been discussed in the policy literature in the ensuing section.

2.8.1 Premium subsidies and agricultural insurance

Farm input subsidies have long been a major policy instrument in a number of DEMCs to increase input demand. The empirical evidence largely shows higher fertilizer application rates in countries with subsidies (Sheahan & Barrett 2017). Garrido & Zilberman (2008) develop a theoretical framework to show how premium subsidies, like other farm inputs, incentivize farmers to participate in agricultural insurance programs. Consistent with the authors' theoretical model, premium subsidies increase insurance participation among Spanish farmers. However, evidence from developing country context has been mixed and inconclusive. For example, in their studies in India, Giné et al. (2008) and Cole et al. (2013) report low participation even after heavily subsidizing premiums. In China, however, the evidence appears to suggest improved participation decisions with subsidies (Cai et al. 2015, Cai 2016). This clearly indicates a careful case-by-case study of insurance subsidy programs in DEMCs because of the potential of other equally relevant variables in influencing participation decisions.

2.8.2 Agricultural policies and insurance

Improving the incidence of food and nutrient security, increasing farm incomes, and decreasing income variability are among the key policy objectives pursued by most policy makers in DEMCs. To achieve these objectives, policymakers often have at their disposal a number of instruments in their toolbox to choose. We briefly document how agricultural insurance may complement or substitute other policy instruments in achieving these policy objectives.

The role of risks and uncertainties as a disincentive to poor farmers in investing in risky agricultural inputs is well known in the literature. Incentivizing farmers to purchase these risk-increasing inputs may be achieved through the provision of input subsidies or relaxing the binding uninsured risk through the provision of insurance. Indeed, many studies have

documented the investment-enhancing role of providing input subsidies (Sheahan & Barrett 2017, Holden 2019). Although the provision of input subsidies may be viewed as a direct solution to addressing the low investments in risk-increasing agricultural inputs, relaxing these risks through the provision of insurance may be an option. Karlan et al. (2014), for example, report increased investments in fertilizer expenditure after a sample of Ghanaian farmers were offered weather-based insurance. To this end, agricultural insurance and input subsidies play a substituting role in achieving increased fertilizer applications, which will eventually lead to improved productivity gains. However, what is not known is the extent to which agricultural insurance can substitute for fertilizer subsidy.

Increasing poor farmers' incomes continue to be at the forefront of most agricultural and development policies of DEMCs. Universal basic income has been proposed as an option. However, the challenge of justifying the prudent use of scarce resources has contributed to only three[6] known DEMCs who have implemented a true unconditional universal income, whereas the others are often targeted, with conditionalities (Banerjee et al. 2019). As previously indicated, farmers' incomes can be increased when the binding uninsured risk is relaxed to spur investments in inputs such as fertilizer to enhance productivity. Here again, agricultural insurance could be considered as an indirect substitute for universal basic income.

2.9 Conclusions and further research

Even though farmers in most DEMCs are highly exposed to risks and uncertainties in the agricultural production, they often lack better tools to manage these risks. Researchers and policy makers have long proposed and implemented agricultural insurance as a tool to mitigate risks that farmers face, with high anticipation of uptake. Yet uptake of insurance has been far

[6]These include some nine villages in the Indian state of Madhya Pradesh, two villages in Namibia, and Iran, which implemented a nationwide cash transfer in response to the withdrawal of food and fuel subsidies (Banerjee et al. 2019).

below expectations. Given the significance of designing policy measures to minimize the risks involved in agricultural production in DEMCs, several studies have sought to understand the main drivers of low uptake. Many of the studies identified lack of trust, liquidity and credit constraints, partial coverage of risks, lack of understanding of the insurance products, and some behavioral factors such as rate of time preference as the main drivers of the low demand for agricultural insurance. Despite the increasing body of research on the topic, some knowledge gaps can be explored in future studies.

It appears that most index-based insurance programs in most DEMCs have largely focused on annual crops, with little attention paid to perennials crops. Despite the fact that designing an index-based insurance program for perennial crops may be technically more challenging, it is still an important avenue for consideration, given that farmers who cultivate perennial crops have an additional challenge of less flexibility in adjusting their production under risky conditions.

Lack of trust has been largely cited as a cause of low demand for agricultural insurance in most DEMCs. Farmers' nontrusting behavior has developed through their past experiences. Thus, past dependence plays a significant role in individuals forming beliefs about an innovation they have little information on. However, the literature on trust has been silent on investigating farmers' past dependencies in forming their distrusting behavior. Therefore, studies should explore how these past dependencies inform farmers' trusting behavior and how to address them to improve insurance uptake.

As research continues on agricultural insurance, particularly index-based insurance, there is the need to collect rich panel data sets to examine the relationship between indices and actual losses incurred in order to improve the prediction accuracies of indices. This would go a long way to reducing the incidence of basis risk that is a critical disincentive factor for farmers in taking up index-based insurance. To the extent that index-based insurance appears to be the

future for the agricultural insurance sector, undertaking this research to refine the indices would improve its uptake and subsequently contribute to the improvement of farmers' welfare.

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Chapter Three

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

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Abstract

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.

Keywords: Crop insurance, risk aversion, ambiguity aversion, liquidity constraints, field experiments

3.0 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 behavioral literature, for example, recognizes 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 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 and 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 fertilizer and enterprises with higher risks (Karlan et al. 2014; Cai 2016). 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 and 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 (Gine et al. 2008; Ali et al. 2020). 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 (Karlan et al. 2014; Cole et al. 2013), 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 (Karlan et al. 2014; Cole et al. 2013). 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 (Casaburi and Willis 2018; Belissa et al. 2020). 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.

Behavioral factors including risks and ambiguity also play relevant roles in agricultural insurance uptake decisions. While risks characterize 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 and 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 and 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 involve ambiguity, such that the probabilities of potential outcomes are unknown (Barham et al. 2014; Bryan 2019). In analyzing the role of risks on farmers' demand for crop insurance, recent studies have argued that the impact of risks need to be isolated from ambiguity (e.g. Bryan 2019; Belissa et al. 2020).

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 and 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 and 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 3.3 outlines the empirical strategy employed in the paper. Section 3.4 describes the data employed in the analysis. Section 3.5 discusses the empirical results. The final section contains conclusions and policy recommendations.

3.1 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 behavioral 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 $f(\mathrm{x},\varepsilon)$, 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 adversarial $\varepsilon_{\min}$ to most favourable $\varepsilon_{\max}$ 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 $\gamma \in [0,1]$.[7] 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 $\max\left[p\left(\gamma\left(\bar{q} - f(x,\varepsilon)\right)\right), 0\right]$, 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 farmers receive an indemnity payment if ε falls below ε^{γ} (Babcock and 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 maximizes 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

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

$\gamma\bar{q}$, the farmer`s net benefits are given as $v^{\gamma} = p\gamma\bar{q} - p_x x - p_h - p_i(\gamma)$, otherwise, the net benefits are given by $v = pf(x,\varepsilon) - p_x x - p_h - p_i(\gamma)$. 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, i.e. $\delta\left(E\left[v^{\gamma} + v\right]\right) - p_i(\gamma) > 0$. 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-contraints will be addressed in the empirical part of this study.

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

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

where U stands for the expression $u\left(\tilde{v}^{\gamma};r\right) + u\left(\tilde{v};r\right)$ that is influenced by the risk preferences r. If the actual yield is below $\gamma\bar{q}$, the farmer's net benefits taking into account the liquidity constraints are denoted by $\tilde{v}^{\gamma}$, and are given by $\tilde{v}^{\gamma} = v^{\gamma} + \mu\left(\delta\left(E\left[v^{\gamma} + v\right]\right) - p_i(\gamma)\right)$ where μ denotes the Lagrange multiplier associated with the farmer's liquidity constraint. If the actual yield is above $\gamma\bar{q}$, the farmer's net benefits taking into account the liquidity constraint are denoted by $\tilde{v}$, and are given by $\tilde{v} = v + \mu\left(\delta\left(E\left[v^{\gamma} + v\right]\right) - p_i(\gamma)\right)$.

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 summarized 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 $h(\varepsilon)$. The weighting process based on the second-order priors $\theta(h(\varepsilon))$ can be seen as a second-order probability distribution (Machina and 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 characterized 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 maximization 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 maximized 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

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

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

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

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.[8] 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, $\frac{d\gamma\bar{q}}{dr}$, or in the ambiguity attitude, $\frac{d\gamma\bar{q}}{d\rho}$. For this reason, we do not attempt to determine the sign of the integral of the expressions $\frac{d\gamma\bar{q}}{dx}, \frac{d\gamma\bar{q}}{dr}$ and $\frac{d\gamma\bar{q}}{d\rho}$, 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.

3.2 Empirical specification

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

$$U_{\gamma}^{**} \equiv \max_{\gamma} \int_{\theta(h(\varepsilon_{\min}))}^{\theta(h(\varepsilon_{\max}))} \varphi\left(E\left(U_{\gamma}^{*}\right);\rho\right) d\theta\left(h(\varepsilon)\right), \text{ subject to } \delta \mathrm{E}\left[v^{\gamma}+v\right] > p_i(\gamma). \tag{5}$$

where $U_{\gamma}^{*} = \max_{x} E\left[U(v^{\gamma}) + U(v)\right]$. 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 $\delta \mathrm{E}\left[v^{\gamma}+v\right] < p_i(\gamma)$ a non-binding term in the maximization problem. Equation (5) provides

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

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

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

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 and Meghir 2017).

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 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

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

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 μ_i the error term.

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

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

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 ν_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 fertilizer 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 and 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 fertilizer 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 boostraped 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.

3.3 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 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), 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 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 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 3.6A in the appendix). 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 categorized into highly risk-averse, moderately risk-averse, risk-neutral and risk-loving.

Table 3. 1: Basis for categorizing 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%)

Notes: 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.

Table 3.1 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 3.8A in the appendix. 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 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 categorization of farmers' ambiguity aversion on their decision

on the box from which they draw the ball. Specifically, a farmer is categorized 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 categorized as being ambiguity averse (see Table 3.2).

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 minimize 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 $p_i \gamma \bar{q}$, where p_i is the projected price, γ is the coverage, and $\bar{q}$ is the average historical district yield. The average historical yield data obtained from COCOBOD was detrended using a weighted moving average 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 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.

Table 3. 2: Descriptive statistics of variables used in the regression models

Variables	Variable description	Mean	S.d
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
Fertilizer Exp.	Fertilizer 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

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

Prior to administering the questionnaires, we organized brief information sessions to farmers in groups not exceeding 10 members. Here, we explained the concept of area-yield insurance using Figure B2 in the appendix. 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 and 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 3.2, while the mean differences between the relevant variables are given in Table 3.3. 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. 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

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

3.4 Empirical results

Table 3.4 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 fertilizer 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 behavior, where the demand for normal goods decline with increasing prices. The estimates for the coefficients of risk preferences, liquidity constraints and the level of fertilizer expenditure variables are individually consistent with our theoretical model, in the sense that the likelihood of participating in crop insurance programs appear to be positively correlated with risk attitudes and fertilizer 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 characterized with substantial uncertainties tend to be less willing to participate in crop insurance programs.

In Table 3.5, 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 fertilizer 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

Table 3. 4: Parsimoniuos 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)
Fertilizer 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 ratio (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

Notes: Standard errors in parenthese. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 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)
Fertilizer 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)
Fertilizer expenditure residual	-0.1719	-0.0532	-0.1441	-0.0464	-0.16904	-0.0523
	(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	

Notes: Bootstrapped standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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.

The estimates, shown in Table 3.5 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 characterizing 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 3.5).

Regarding the estimates in Table 3.5, 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 fertilizer have a higher tendency to participate in crop insurance programs. This is not surprising, given that the economic benefits of fertilizer application are often contingent on the random state of nature, particularly on timely rainfall. In a bad state of nature, applying chemical fertilizer will further reduce farmers' expected profits, because the crops will not make use of the applied fertilizer for productive gains. However, in a good state of nature, farmers' expected profits increase. Therefore, applying chemical fertilizer increases the variation in the expected profits. It is not surprising that farmers whose spending are relatively high on chemical fertilizers 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 3.6. Column 1 presents estimates of risk and ambiguity preferences, as well as liquidity constraints and fertilizer expenditure, while in column 2 estimates of these variables and other covariates are presented. The results from the first column indicates that even though the effects of ambiguity aversion on its own is qualitatively similar to our previous estimates, it is not statistically significant. Regarding estimates of interaction 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.

Table 3. 6: Interaction effects of risk and ambiguity aversion, and fertilizer 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)
Fertilizer 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)
Fertilizer 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***	
Deg. of freedom	14		15	
Observations	750		750	

Notes: 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

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 and 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 (Gine 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 (Hill et al. 2013).

3.5 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 minimizing 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 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 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 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 insurance packages.

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Appendices

Table 3. 5A: 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

Notes: Farmers were presented with option of choosing between two mutually exclusive options for each of the three games. In each game, they were presented with a riskless option of GH₵ 20 and a risky one, with amounts of GH₵ 40, GH₵ 24 and GH₵ 50 with half ($P = 0.5$) chance of winning that or not winning anything.

Table 3. 6A: Risk experiment game set-up with expected values

Game	**Lottery option A**		**Lottery option B**		Difference
	Option A	EV_A	Option B	EV_B	$EV_B - EV_A$
Game 1	100% of GH₵20	GH₵20	50% of GH₵40	GH₵20	0.0
Game 2	100% of GH₵20	GH₵20	50% of GH₵24	GH₵12	- 8.0
Game 3	100% of GH₵20	GH₵20	50% of GH₵56	GH₵28	+ 8.0

Notes: **EV** refers to the expected value of the probable option. It is the sum of the product of the probability of winnings and value of the winning, and probability of losing and the value of the lossing. Given that the value of losings is 0 for each of the 3 games and the constant probability of 0.5, the expected value is half the value of winnings in lottery option, B.

Table 3. 7A: Ambiguity aversion elicitation game

Game	Risk Option (Box **A**)	Ambiguous option (Box **B**)
Game 1	100% win GH₵ 20 or GH₵ 0	"Unknown" % win GH₵ 20 or GH₵ 0
Game 2	80% win GH₵ 20 or GH₵ 0	"Unknown" % win GH₵ 20 or GH₵ 0
Game 3	50% win GH₵ 20 or GH₵ 0	"Unknown" % win GH₵ 20 or GH₵ 0
Game 4	30% win GH₵ 20 or GH₵ 0	"Unknown" % win GH₵ 20 or GH₵ 0
Game 5	10% win GH₵ 20 or GH₵ 0	"Unknown" % win GH₵ 20 or GHC 0
Game 6	0% win GH₵ 20 or GH₵ 0	"Unknown" % win GH₵ 20 or GHC 0

Notes: The same order of presentation was maintained for all, to reduce the incidence of potential biases of choice architecture on subjects' decisions. To limit the incidence of anchoring bias, we interspersed the risk and ambiguity games with the trust and loss aversion games.

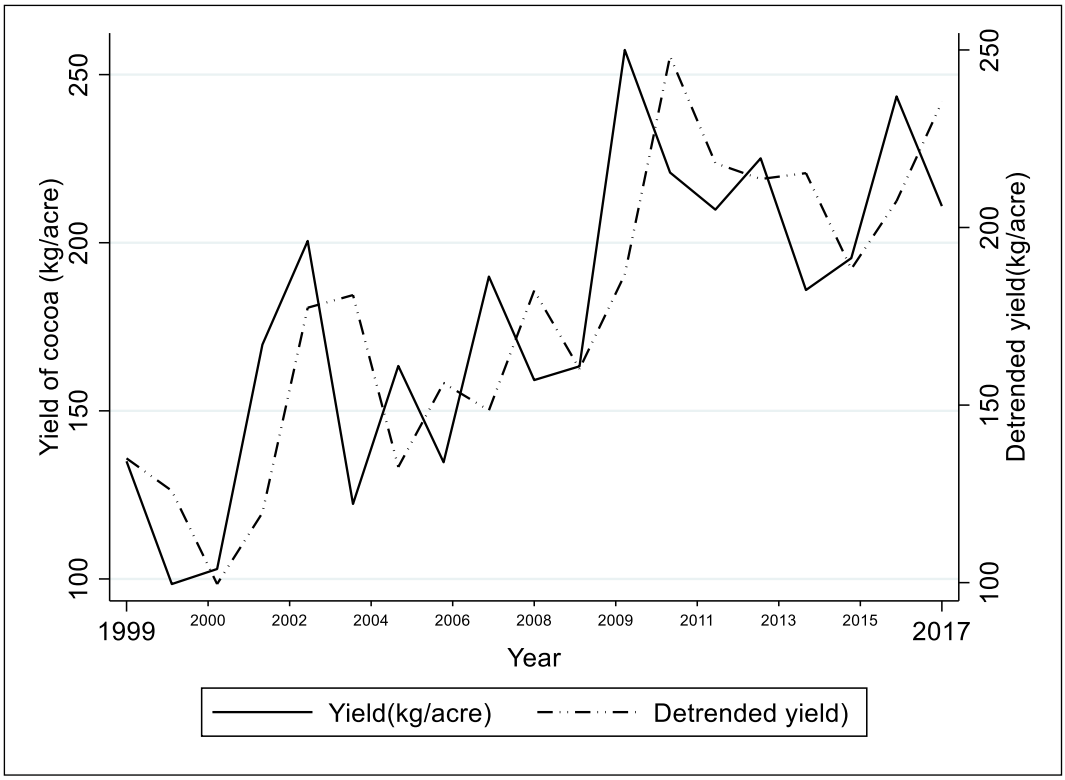

Figure 3. 1A: Historical cocoa yields (with/without trends) 1999 to 2017 (kg/acre)

Table 3.8A: Descriptive on historical yield data

Variable	Mean	Std. dev.
Yield (1999-2017)	178.33	45.58
Yield_detrended (1999-2017)	175.34	41.69

Notes: We use 3-year preceding yield values for detrending.

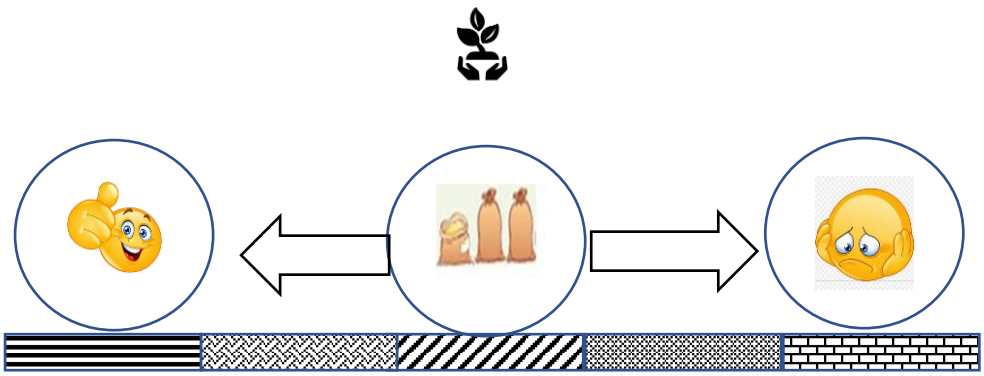

Figure 3. 2A: A sample of demonstration for explaining the index-based insurance

Chapter Four

Delayed premium payments improve crop insurance uptake, but at what costs? The role of time preferences

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Abstract

Recent studies recommend deferred insurance premium payments until harvest, in order to increase uptake of crop insurance among liquidity-constrained farmers. However, crop insurance purchases do not only transfer incomes from a good to a bad state of nature, but also across time. Hence, the extent to which individuals' trade-off present consumption desires for the future may affect crop insurance uptake decisions. In this study, we investigate the impact of time preferences on the uptake of a heterogeneous Ideal Area Yield (IAYI) Insurance product, using a sample of cocoa farmers from Ghana. We employ field experiments to elicit farmers' time preferences and characterize them with the quasi-hyperbolic discounting. We then use linear and quantile regressions to analyze the drivers of time preferences measure. Finally, we employ a hybrid choice model to jointly estimate attributes of the insurance product, farmers' stated attribute non-attendance (ANA), and some attitudinal variables, while accounting for potential endogeneity bias. The empirical results indicate that while the short-run measure of time preferences significantly decrease the demand for attributes of the insurance product, the long-run measure appears to enhance demand. Farmers also tend to favor insurance products with delayed payments until harvesting.

Keywords: Ideal area yield insurance, quasi-hyperbolic discounting, rate of time preferences, field experiment

JEL Codes : E21, G22, G52, Q18

4.0 Introduction

Economic theory postulates that risk-averse farmers, often exposed to significant production risks, have strong incentives to trade-off their risks through agricultural insurance that indemnifies production losses. However, in reality, numerous empirical studies find evidence that appears to be inconsistent with theoretical propositions, particularly in developing countries (Karlan et al. 2014; Ali et al. 2020; Liu et al. 2020). These puzzling findings commend researchers and policy makers to ask for the underlying factors for the low demand for agricultural insurance despite farmers' aversion to risks. A plethora of studies has sought to improve our understanding of the underlying causes for the low demand for agricultural insurance by focusing on the role of income transfers across states of nature (Mobarak and Rosenzweig 2012; Dercon et al., 2014; Carter et al., 2016; Ceballos and Robles 2020). In the last decade, a growing body of literature suggests that agricultural insurance not only transfer incomes from a good to a bad state of nature, but also across time (Liu and Myers 2016; Casaburi and Willis 2018; Liu et al., 2020).

In this paper, we contribute to the emerging evidence on the role of agricultural insurance in income transfer across time, by investigating the influence of time preferences on crop insurance uptake decisions in Ghana. In particular, we explore the effect of farmers' time preferences on crop insurance uptake decisions for dynamically inconsistent farmers.[9] Inconsistency of time preferences may lead to circumstances where it is optimal to purchase insurance in period $t+1$, but when this period becomes the current period, it may no longer be optimal due to stronger discounting of current time preferences than future time preferences, leading to present bias preferences (Ai et al. 2016).

[9] For example, in the case of hyperbolic time preferences the discount rate in period t is higher than in period $t+1$.

The issue of time preference is significant in analyzing crop insurance, because insurance contracts typically require a farmer to make upfront premium payments, but only receive state-dependent indemnity payments from the insurance at a later point in time. Traditionally, initial upfront premium payments occur at the beginning of the cropping season when farmers are usually cash-strapped, and any subsequent indemnity payment occurs at harvest times when farmers are less liquidity constrained. Thus, farmers who are liquidity-constrained could face financial problems, if they purchase crop insurance at the beginning of the cropping season. Yet, the possible economic costs of farmers' exposure to production risks without appropriate adaptation and mitigation measures can be quite significant. Hence, crop insurance can be considered as a promising financial instrument to reduce these costs (Dercon 2004; Kukk and Kulikov 2016). To relax temporal liquidity constraints and increase uptake of crop insurance, recent studies suggest that the costs of insurance payments be deferred until crop harvest, when farmers are less likely to face liquidity problems (Casaburi and Willis 2018; Belissa et al. 2019). However, when farmers' behavior is time inconsistent, it could undermine their interests in following through with the planned decisions to pay at harvest, putting the viability of the insurance product into question.

Given the importance of risk aversion and time preferences for insurance uptake, the principal objective of this study is to analyze to what extent the dynamics of time preferences interfere with risk aversion for the uptake of crop insurance. The study further investigates the role of loss aversion described as cognitive biases of strong disutility for losses relative to the utility of gains on crop insurance uptake decisions (Hwang 2021). Crop insurance demand will be decreasing in the level of loss aversion, if a farmer perceives crop insurance as an investment rather than a yield risk-hedging tool, and also if premiums are paid, but there are no indemnity receipts. On the other hand, crop insurance demand will be increasing with the level of loss aversion for a farmer who considers the risk-hedging role of crop insurance.

Our study is not unique in its interest in the role of time preferences and risk aversion in the decision-making process of farm households. Given its significance, the issue of time preferences and outcomes of economic decisions has received considerable attention in the theoretical and empirical literature (Cawley and Ruhm 2012; Andreoni and Sprenger 2012; van Huiven and Alessie 2015; Newel and Siikamäki 2015; Bradford et al., 2017). At the household level, for example, Duflo et al., (2011) document the significant role time preferences play in fertilizer use decisions among a sample of Kenyan farmers. In their study on disease management, Watts and Segal (2009) attribute the rather myopic government health policies on acute and curative care instead of focusing on preventive health care to the high discount rates among policy makers in developing countries. Other studies have found evidence of the consumption of addictive substances and dieting lifestyle behaviors to be highly related to discount rates, indicating the crucial role discount rates play in nearly all human behaviors (Becker and Murphy 1988; Olsen 1993; Cawley 2008; Adams and White 2009; Cawley and Ruhm 2012). As indicated earlier, farmers with low rates of time preferences trade off minimally current and future values, and therefore, are likely to purchase insurance to hedge against future production losses. On the other hand, farmers with high rates of time preferences discount future production losses notably and are not likely to purchase crop insurance, even if they are risk averse. Thus, farmers' aversion to risk is a necessity for the decision to take up crop insurance, but the mediating role of time preferences could interfere with insurance uptake decisions.

The current literature on agricultural insurance is frequently theoretical (Gollier 2003; Liu and Myers 2016), and empirical analyses on the influence of time preferences on insurance uptake decisions are scant. In their study on risk and time preferences in Mali and Burkina Faso, Liebenehm and Waibel (2014) found time preferences to be correlated with wealth, education, and religion. In a more recent study, Hill et al. (2019) examined the impact of

discounts (instant reduction of purchase price) and rebates (later refund of purchase price) on insurance demand, and found that discounts had greater impacts relative to rebates. Even though these findings present some insights into the relevance of time preferences in the demand for crop insurance, the study did not address the influence of non-constant and present biased time preferences on crop insurance uptake decisions.

In the present study, we employ a discounted utility model to examine the time preferences of cocoa farmers. The analysis allows us to gain insights into how intrapersonal dynamics of time preferences influence the demand for attributes of cocoa insurance product. We use hyperbolic discounting to characterize time preferences. To the best of our knowledge, this is the first study to explicitly relate intrapersonal measure of time preferences to crop insurance uptake, using data from a developing country. Examining the impact of intrapersonal dynamics of time preferences on demand for crop insurance attributes provides insights into farmers' commitments to their decisions, given the recent recommended deferred premium payments to improve crop insurance uptake (Casaburi and Willis 2018).

Since standard index-based insurance products ignore farmers' heterogeneous risks profiles, they are not highly valued by farmers (Ceballos and Robles 2020). Therefore, we consider ideal area yield insurance (IAYI), since it can account for the heterogeneity in risk profiles of farmers, while maintaining the low administrative costs of index-based insurance products. Moreover, the individual risk profiles of the farmers can be adequately captured, since farmers can choose the critical minimal yield that triggers indemnity payments (Miranda 1991; Lichtenberg and Iglesias 2022). Thus, IAYI avoids information asymmetry problems that arise in standard index-based insurance products.

In the absence of agricultural insurance products on the Ghanaian market, we employ field experiments and discrete choice models to examine farmers' uptake decisions. We address

the potential endogeneity problems arising from including farmers' stated attribute non-attendance (ANA) by using a hybrid model. We also employ both linear and quantile regressions to estimate the drivers of time preferences. Our results show that farmers' short-run discount rates significantly decrease their demand for crop insurance attributes, while the long-run discount rates increase their demand. The level of loss aversion tends to increase with utility derived from crop insurance attributes. We also find that income levels, health status, the level of alcohol consumption are key drivers of farmers' short-run discount rates.

The rest of the paper proceeds as follows: section 4.1 presents the theoretical framework, while section 4.2 outlines the empirical framework and specifications. The context, study area and data collection are presented in section 4.3. Section 4.5 contains the empirical results and discussions, while conclusion and implications are presented in the final section.

4.1 Theoretical model

The model we present in this section analyzes how risk and time preferences affect insurance uptake decisions within a dynamic framework. It largely builds on the seminal work by Deaton's (1991) and Caroll et al's (1992) buffer stock consumption model. We consider a risk-averse cocoa farmer who owns a hectare of productive cocoa farm. The productive cocoa farm is characterized by the production function $g(x_t, \mu)$ that generates stochastic farm income y_t, where x_t represents a vector of inputs and the subscript t is the time period. Given that a typical cocoa plantation may be productive in excess of 60 years, usually outliving the cultivator, we further assume that the farmer will either live forever or is altruistic. The stochastic income from production, y_t is assumed to be strictly positive, i.e., $y_t > 0$. Let z_t denote the value of the farmer's liquid assets such as livestock, stored harvests from previous seasons, etc. To the extent that these assets can be sold to generate cash, wealth at the beginning

of each period , w_t, is the sum of the value of the liquid assets, z_t, and any realized state-dependent income, y_t, i.e., $w_t = z_t + y_t$.

Consider a cocoa yield insurance program, such that a loss of magnitude $\bar{L}$, with an associated probability σ of triggering payments to farmers who purchase the program. The farmer has a prior on σ. However, it is so imprecise for a farmer with above average yield losses to self-select into the yield insurance program, so that the adverse-selection problem is minimized.

If the farmer purchases insurance coverage in period t, available income for current consumption, c_t decreases by the payment of the insurance premium, p. Thus, the available wealth in period t is an element of the set $\{w_t - c_t, w_t - p - c_t\}$. Conditional on the probability of yield losses σ, the cocoa farmer may receive indemnity income from the insurance purchase, $i_t(y_{t-1})$, such that the wealth in period $t+1$ is $w_{t+1} = r(w_t - c_t - \phi_{p_t} p) + \phi_{p_t}\phi_{i_{t+1}} i_{t+1}(y_t) + y_{t+1}$, where ϕ_{p_t} and $\phi_{i_{t+1}}$ are binary indicators which are respectively equal to 1, if an insurance premium is paid in period t, and an indemnity is received at time $t+1$, otherwise the two factors are equal to 0 in both scenarios. Under perfect credit market conditions, financial arbitrage argument suggests that a farmer should discount future payments with the opportunity cost of capital, r. However, most developing countries' credit markets are characterized by imperfections (Bauer et al. 2012), resulting in significant differences in individual discount rates and opportunity cost of capital. The farm income is assumed to be independently and identically distributed over time.

We assume that farmers apply quasi-hyperbolic discounting to express the present values of future values.[10] Quasi-hyperbolic discounting starting at $t = 0$ can be based on a discrete-time discount function given by $\{1, \beta\delta^1, \beta\delta^2 \beta\delta^3 ....\}$, where $0 < \beta < 1,\ 0 < \delta \leq 1$ (Harris and Laibson 2001). In contrast, exponential discounting assumes $\beta = 1$, so that the discount factor δ is constant over time. From the perspective of period 0, the quasi-hyperbolic discount factor between period 0 and 1, is the short-term discount factor given by $\beta\delta$, while the long-run discount factor is δ . The higher value of the short-term discount factor compared to the lower long-term discount factor creates dynamically inconsistent preferences (Harris and Laibson 2001). Discrepancies arise if values of a future period that were initially discounted with the long-run discount factor δ are revaluated with the short-run discount factor, $\beta\delta$ when the future period becomes the current period. This implies that the initial long-run preferences may not be maintained as future periods become current periods.

For the following analysis, we focus on stationary perfect Markov equilibria, i.e., decisions are influenced by the current state, but not by the past states. We define the consumption and the binary choice variable of insurance uptake which satisfy the equilibrium condition at any period t by $C(w_t, p)$ and $\Phi_{p_t}(w_t, p)$. To analyze the farmer's decision problem of insurance uptake, we formulate the underlying continuation-value function V . The evaluation of V allows the farmer to make rational choices. From the perspective of a farmer at period t, the discount factor from period $t+1$ onwards will be δ, and therefore the continuation value function V from period $t+1$ onwards is given by

[10] For analytical convenience, we assume in this section quasi-hyperbolic discounting. Yet, for the empirical part we allow for a non-constant discount factor not only during the time periods 0 and 1, but also thereafter.

$$V(w_{t+1},p)=U\left(C\left(w_{t+1},p\right)\right)+E_{t+1}\left[\delta V\begin{pmatrix} r\left(w_{t+1}-C\left(w_{t+1},p\right)\right) \\ +\Phi_{p_{t+1}}\left(w_{t+1},p\right)\phi_{i_{t+2}}i_{t+2}\left(y_{t+1}\right)+y_{t+2}\end{pmatrix}\right]. \tag{4.1}$$

For any given value of liquid asset w_{t+1} and insurance premium p, the value function V recursively solves equation (1) from period $t+1$ onwards. At period t the farmer's current value function $\hat{V}\left(w_t,p\right)$, can be expressed as:

$$\hat{V}(w_t,p)=U\left(C\left(w_t,p\right)\right)+E_t\left[\beta\delta V\left(r\left(w_t-C\left(w_t,p\right)\right)+\Phi_{p_t}\phi_{i_{t+1}}i_{t+1}\left(y_t\right)+y_{t+1}\right)\right]. \tag{4.2}$$

At every period t, the farmer decides how much of her liquid assets should be spent on consumption goods, and crop insurance. Thus, the farmer's decision problem at period t can be written as

$$\left\{C\left(w_t,p\right),\Phi\left(w_t,p\right)\right\}\in\underset{c\in\left[0,w_t-\phi_{p_t}p_t\right],\,\phi_{p_t}\in\{0,1\}}{\arg\max}\quad U\left(c\right)+E_t\left[\beta\delta V\left(r\left(w_t-c-\phi_{p_t}p\right)+\phi_{p_t}\phi_{i+1}\left(y_t\right)+y_{t+1}\right)\right]\ . \tag{4.3}$$

For given w_t, p equation (4.3) defines optimal level of consumption C and the optimal decision Φ_{p_t} to contract insurance or not. However, equation (4.3) does not define $C(w_t,p)$ and $\Phi(w_t,p)$ by an equal sign as it includes all possible values of w_t and p. The first-order condition of equation (4.3) with respect to c evaluated at the optimal values of the decision variables[11] implies that

$$U'\left(C\left(w_t,p\right)\right)\geq E_t\left[r\beta\delta V'\left(r\left(w_t-C\left(w_t,p\right)-\Phi_{p_t}\left(w_t,p\right)p\right)+\Phi_{p_t}\left(w_t,p\right)\Phi_{i_{t+1}}i_{t+1}+y_{t+1}\right)\right]. \tag{4.4}$$

According to equation (4.4), the left-hand side is either greater than or equal to the right-had side terms. Strict equality of the terms on the left- and right-hand sides is only obtained if the

[11] Since the variable ϕ_{p_t} is binary its optimal value $\Phi(w_t,p)$ is not defined by a first-order condition but by the value of ϕ_{p_t} that yields the highest value of the value function V.

level of consumption is less than current wealth minus any insurance premium payment, i.e., $C\left(w_t, p\right) < \left(w_t - \Phi_{p_t} p\right)$.

Since the first-order condition (4.4) holds for any values of w_t and p, the envelope theorem guarantees that an increase in wealth expressed by the current value function $\hat{V}$ corresponds to the marginal utility with respect to consumption,

$$\hat{V}'\left(w_t, p\right) = U'\left(C\left(w_t, p\right)\right).$$

(4.5)

Moreover, by the definitions of $\hat{V}(w_{t+1}, p)$ and $V(w_{t+1}, p)$ it holds that

$$\beta V\left(w_{t+1}, p\right) = \hat{V}(w_{t+1}, p) - \left(1-\beta\right) U\left(C\left(w_{t+1}, p\right)\right). \tag{4.6}$$

Differentiation of equation (4.6) yields

$$\beta V'\left(w_{t+1}, p\right) = \hat{V}'(w_{t+1}, p) - \left(1-\beta\right) U'\left(C\left(w_{t+1}, p\right)\right) C'\left(w_{t+1}, p\right). \tag{4.7}$$

Substituting the expression of $\beta V'\left(w_{t+1}, p_t\right)$ into (4.4) shows that

$$U'\left(C\left(w_t, p\right)\right) \geq E_t\left[r\delta\left(\hat{V}'(w_{t+1}, p) - \left(1-\beta\right) U'\left(C\left(w_{t+1}, p\right)\right) C'\left(w_{t+1}, p\right)\right)\right].$$

Utilizing equation (4.6), we obtain

$$U'\left(C\left(w_t, p\right)\right) \geq E_t\left[r\delta\left(U'\left(C(w_{t+1}, p)\right) - \left(1-\beta\right) U'\left(C\left(w_{t+1}, p\right)\right) C'\left(w_{t+1}, p\right)\right)\right].$$

Rearranging terms we have

$$U'\left(C\left(w_t, p_t\right)\right) \geq E_t r\left[\left(C'\left(w_{t+1}, p_t\right)\beta\delta - \left(1 - C\left(w_{t+1}, p_t\right)\delta\right) U'\left(C(w_{t+1}, p_t)\right)\right)\right],$$

$$\frac{U'\left(C\left(w_t, p\right)\right)}{U'\left(C(w_{t+1}, p)\right)} \geq E_t r\left[C'\left(w_{t+1}, p\right)\beta\delta + \left(1 - C'\left(w_{t+1}, p\right)\right)\delta\right]. \tag{4.8}$$

Equation (4.8) indicates that the effective discount factor is averaged over the short-run discount factor $\beta\delta$ and the long-run discount factor δ. The weights are given by the terms

$C'(w_{t+1}, p)$ and $1-C'(w_{t+1}, p)$. The effective discount factor is less than δ, whereas for exponential discounting where $\beta = 1$, it is equal to δ. Hence, we observe that

$$\frac{U'(C(w_t, p))}{U'(C(w_{t+1}, p))} \geq r\beta\delta . \tag{4.9}$$

Observation: The demand for insurance coverage decreases with a decrease in the discount factor β.

The observation indicates that as the discount factor increases, the marginal rate of substitution of marginal utilities of present relative to future consumption decreases. The sign and magnitude of the relationship between the discount factors and insurance demand will be examined in the empirical section.

4.2 Empirical framework and specification

In this section, we outline the specification to analyze the effects of time preferences on farmers' preferences for crop insurance attributes, using the standard random utility framework, and drawing on the theoretical model outlined in the previous section. In line with the first-order conditions in the theoretical model in equation (4.5), a farmer h evaluates a number of alternatives of crop insurance products i under choice scenarios s that maximizes her unobserved utility U_{ihs}. The unobserved utility that the farmer derives is expressed as a function of both a measurable deterministic part, $D_{ihs}(\cdot)$ and a stochastic component ε_{ihs} that varies with the state of nature, assumed to be independently and identically distributed (*i.i.d.*). The deterministic part is composed of observed attributes of the insurance product, x_{ihs}, farmer-specific characteristics, including time preferences, ϑ_h, and the estimated taste parameters κ, and can be expressed as $U_{ihs} = D(x_{ihs}, \vartheta_h; \kappa_i) + \varepsilon_{ihs}$. A farmer only chooses an alternative insurance product i, if the utility derived from it is greater than utility from any

other alternative, including non-purchase in the choice set, i.e. $U_{ihs} > U_{jhs}$ for all alternatives with $j \neq i$.

It is worth pointing out that an otherwise complex decision-making maybe undertaken in a simplified decision rule (Scarpa et al. 2013; Hensher et al. 2015). Under this simplified decision-making rule, termed heuristics, farmers have the tendency to ignore some of the attributes by not attending to them (attribute non-attendance (ANA)) in the crop insurance choice decisions. ANA results in biased estimates when not accounted for. In line with Hess and Hensher (2013), we model ANA as:

$$\tau_{h\kappa} = \psi_{\kappa} \vartheta_h + \iota_{hk} , \tag{4.10}$$

where $\tau_{h\kappa}$ is the ranking of an attribute x_{ih} by farmer h, ϑ_h is farmer-specific characteristics including time preferences, ψ_{κ} are parameters of the ANA to be estimated and ι_{hk} denotes the error term.

Similarly, certain innate attitudes and perceptions could be driving farmers' crop insurance decisions. In particular, farmers' risks attitudes and perceptions about insurance could be driving choices that may also bias our parameter estimates, and therefore need to be accounted for in the deterministic part of the choice model. Incorporating risk attitudes and crop insurance perception, as well as ANA gives:

$$U_{ihs} = D\left(x_{ihs}, \vartheta_h, \tau_{hk}, \psi_h\right) + \varepsilon_{ihs} \tag{4.11}$$

Now, the probability of a farmer choosing an alternative, conditional on her specific farm and household characteristics including time preferences, attributes of the insurance product, attribute processing information, risk attitudes and perception of insurance is:

$$\Pr\left(\text{choice}_{hs} = i \middle| \kappa_{hs}, \tau_{\kappa s}, \psi_h, \vartheta_h\right) = \frac{\exp^{\exp\sum_{i=1}^{I}(\tau_{hk}\psi_h\vartheta_h)\kappa_{ihs}}}{\sum_{i=1}^{I}\exp^{\exp\sum_{i=1}^{I}(\tau_{hk}\psi_h\vartheta_h)\kappa_{ihs}}} \tag{4.12}$$

The underlying empirical specification is presented as:

$$\begin{aligned} u_{ihs} = {} & \kappa_i \begin{bmatrix} \text{Coverage}_{ihs} + \text{CriticalYield}_{ihs} + \text{Government}_{ihs} + \text{Private}_{ihs} + \text{LBCs}_{ihs} + \text{Private}_{ihs} \\ + \text{Harvest}_{ihs} + \text{Planting}_{ihs} + \text{Premium}_{ins} \end{bmatrix} \\ & + \vartheta_h \left[\text{RTPBETA}_h + \text{RTPDELTA}_h + \text{Fem}_h + \text{ReadWrite}_h + \text{Coshare100}_h\right] \\ & + \tau_h \left[\text{YCIP1}_h + \text{YCIP2}_h + \text{YCIP3}_h + \text{YCIP4}_h + \text{YCIP5}_h\right] \\ & + \psi_h \begin{bmatrix} \text{CoverageANA}_h + \text{CriticalYieldANA}_h + \text{ManagementANA}_h + \text{PeriodANA}_h \\ + \text{PremiumANA}_h \end{bmatrix} \\ & + \ [\text{constant}] \\ & + \varepsilon_{ihs} \end{aligned} \tag{4.13}$$

Where $Coverage_{ihs}$ refers to the level of insurance coverage, $CriticalYield_{ihs}$ is the critical yield that triggers indemnity payments, $Government_{ihs}$ 1 if insurance is managed by government, $Private_{ihs}$ 1 if insurance is privately managed, LBC_{ihs} 1 if managed by a licensed buying company, $Harvest_{ihs}$ 1 if insurance premiums are paid at harvesting time, $Planting_{ihs}$ 1 if premium is paid during planting season, $Premium_{ihs}$ is the cost paid per acre of land insured $RTPBETA_h$ and $RTPDELTA_h$ are respectively short-run and long-run measures of rate of time preferences. $YCIP_h$ are farmers' perceptions on their yield risks and insurance as described in Table 4.1. $CoverageANA_h$ is farmers' reported attribute non-attendance on coverage, $CritialYieldANA_h$ reported attribute non-attendance on critical yield, $ManagementANA_h$ is the attribute non-attendance to the manager of the product, $PaymentANA_h$ is that for non-attendance to time of payment, $PremiumANA_h$ is the attribute non-attendance to premium, and ε_{ins} is the random noise. The variable description and summary statistics are presented in Table 4.4

4.3 Context, study area and data collection

4.3.1 The context

Cocoa is a perennial tree cash crop cultivated largely in the middle to southern belt of Ghana. The sector has a long history of projecting the country into lime light. Even though Ghana is the second leading producer of Cocoa worldwide, after Cote D'Ivoire, it has the reputation of producing high quality beans (Roldan et al., 2013). Incomes from cocoa export make up about one-fifth of Ghana's exports earnings. The sector supports about four million farming households (ISSER 2017), and contributes between 70 - 100 percent of their total annual incomes (Läderach et al. 2013).

However, like other sectors of agriculture in Ghana, cocoa farmers are experiencing the negative effects of climate shocks (Bunn et al., 2019). Dry season temperatures have seen dramatic increases, resulting in increased evapotranspiration (Läderach et al., 2013; Schroth et al., 2016). Rains have become erratic, with increased variability (Bunn et al., 2019). Currently, these erratic climatic factors tend to drive cocoa yields down through the increased disease and pest incidence (Läderach et al., 2013; Amfo and Ali 2020; Cilas and Bastide 2020). Bunn et al., (2019) simulated climatic conditions for 2050s and observed that large portions of the land currently under cocoa cultivation will not be suitable. Farmers' livelihoods are therefore at stake if policy changes are not instituted to address these emerging challenges.

Further compounding the challenge is the recent increased activities of artisanal gold mining (ASM), locally referred to as *galamsey* in cocoa growing areas of Ghana. The presence of ASM activities in cocoa growing communities tend to have negative externalities on the activities of farmers. It may be argued that ASM generate incomes for those involved, but they tend to distort factor markets. For example, the presence of ASM activities tend to distort factor

markets by increasing the cost of hired labor, for example. Under such high wages, farmers with limited finances find it difficult to hire labor to undertake relevant and timely production practices. Cocoa yields could significantly decline because most of the production practices do not lend themselves to mechanization. In extreme circumstances, farmers are compelled to sell out cocoa plantations to the miners, because of lower productivity (Woods 2018).

4.3.2 The study area

The survey was conducted in the three largest cocoa-producing regions in Ghana, at the farm household-level between April and July 2018. The Ashanti, Brong-Ahafo and Western regions constitute our regions of study. Currently, the Western region produces more than half of Ghana's cocoa. Following the Western is the Ashanti region where about one-fifth of the cocoa production occurs. 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), 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 of Ghana. Four districts were selected from the Western region and two districts each from Ashanti and Brong-Ahafo regions to ensure proportional sampling. Aowin, Sefwi-Akontombra, Sefwi-Juaboso and Bia West constitute the districts from the Western region. The two sampled districts from the Ashanti region were Ahafo-Ano North and Bosome-Freho districts. Finally, 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 regions, respectively. In all, 750 households from 24 villages were sampled across the three-leading cocoa-producing regions.

4.4 Data collection

This section describes the procedure through which the data used in this analysis were generated. We first present a subsection that briefly describes the insurance product, and the discrete choice experiment design. This is followed by a subsection that outlines how data on time preferences measure and loss aversion were generated.

4.4.1 The insurance product and choice experiment design

The traditional (or indemnity-based) insurance where products are made individual-specific is characterized by hidden action and hidden information, making them less appropriate for developing countries. In particular, hidden action (moral hazard) that describes a farmer's tendency to behave opportunistically after insurance take-up is widespread in many developing countries. In addition, the lack of accurate information makes it difficult for insurance companies to accurately characterize farmers on the basis of their risk profiles in order to price discriminate. This often renders high-risk individuals purchasing insurance, so that in the event that losses occur, insurers face high loss ratios, putting the sustainability of the insurance product into question.

Area yield insurance, one of the index-based insurance products, is designed to address the associated challenges of moral hazard and adverse selection with the indemnity-based products. However, the tendency for a farmer to incur losses, and not be indemnified because of the weak relationship between the indemnity-triggering index and farmer's actual losses, termed basis risk, has weakened the demand for insurance (Mobarak and Rosenzweig 2013; Jensen et al., 2018). Therefore, there has been increased attention to minimize the incidence of basis risks (Ye et al., 2019).

The Ideal Area Yield Insurance, described as a hybrid product, leverages the strength of the index-based insurance and that of the indemnity-based insurance (Smith et al., 1994; Mahul 1999). In particular, farmers have the option of choosing some critical yield to inform their premium payments and indemnity receipts. Given the absence of crop insurance programs in Ghana, we use discrete choice experiment to examine the preferences for attributes of the IAYI.

The discrete choice experiment (DCE) consists of five attributes namely critical yield, coverage, management of the product, payment period and the premium, which represents the cost of the insurance product. To obtain values of critical yield, we used a 3-year lag to compute moving averages on 17-year yield data obtained from Ghana Cocoa Board (COCOBOD). Based on Smith et al. (1994), three levels of the coverage attributes are used. These are 25%, 50% and 75% of the yield risk that farmers would incur. Through a series of focus group discussions and comprehensive literature review, three levels of the insurance management are included in the design of the choice sets. They include government, private insurers and licensed buying companies (LBCs). The two levels of payment period include farmers making payments at harvest or at the planting season. It must be pointed out that attributes such as management and period of payment were dummy coded.

To reduce respondent fatigue in designing our choice sets, we used the D-optimal design instead of the full factorial. The choice sets were constructed with two alternatives, and "an opt-out" or "no-buy" option. In order to improve farmers' understanding of attributes and levels of the insurance product, we used pictorial illustrations for the choice cards.

The design generated two insurance alternatives "*X"* and "*Y*", and a "*No Buy*" option. Even though the incidence of hypothetical bias in stated DCE presents a major drawback in obtaining accurate willingness-to-pay estimates, Kesternich et al., (2013) found similar

significance of attributes and their sign of influence for the stated DCE and the real world revealed preference case. Despite this, we took steps to minimize the incidence of hypothetical bias through a cheap talk script, where we informed farmers to make decisions as they would in their real-world scenario. This may not completely eliminate issues of hypothetical biases, but evidence suggest that it significantly minimizes these potential biases (Bello and Abdulai 2016), as such, provides relevant sources for information for consumer behavior assessment.

Table 4. 1: Farmers underlying attitudes toward yield risk and crop insurance

		Items	Strongly disagree (1)	disagree (2)	Indifferent (3)	Agree (4)	Strongly agree (5)
1.	YCIP1	I obtain on average ***lower*** yields (bags/acre) compared to other farmers in this community.	93 (12%)	226 (30%)	66 (9%)	210 (28%)	156 (21%)
2.	YCIP2	Over the past five years, I have observed significant variation in the yields obtained compared to others in this community.	120 (16%)	91 (12%)	173 (23%)	287 (38%)	79 (11%)
3.	YCIP3	I expect my yields to significantly decrease in the near future.	69 (9%)	147 (20%)	67 (9%)	392 (52%)	75 (10%)
4.	YCIP4	There is no need for crop insurance because government will come to our aid should disaster strike.	170 (23%)	241 (32%)	86 (11%)	195 (26%)	58 (8%)
5.	YCIP5	Crop insurance will be important in the future (e.g., 10 years) and ***Not*** now.	159 (21%)	405 (54%)	49 (6%)	79 (11%)	58 (8%)

Notes: This table presents frequencies and percentages of farmers' yield and crop insurance perceptions. Percentages scores are in parentheses.

Five statements were used to measure farmers' yield risks, and crop insurance perceptions. This was aimed at measuring the underlying latent construct that could be driving farmers' preferences for attributes of the insurance product. To undertake this, we used Likert scale to measure the farmer's level of (dis)agreement with these attitude statements. These statements and their response frequencies are presented in Table 4.1.

4.4.2 Time preferences

As rightly noted by Ubfal (2016), eliciting time preferences is quite challenging, since many contextual factors that may influence the results need to be considered. For example, should time preference parameters be elicited over "goods" or "money"? Some authors have

argued that eliciting time preferences over goods present a direct measure of consumption utilities (Cohen et al., 2020). However, using the good-measure presents a major challenge for the purposes of generalization, since different goods usually generate different time preference measures (Ubfal, 2016). To address this challenge, a number of studies use the money-measure of utility (Reuben et al., 2010; Andersen et al., 2014). Despite its' weakness of assuming a linear utility, it provides the most universally representative measure (Ubfal 2016; Dean and Sautmann 2021). We used the hypothetical case of the money-earlier or later (MEL) approach for obvious budgetary reasons. In so doing, we assume that farmers' choices are devoid of outside conditions. As Frederick et al., (2002) rightly point out, this narrow bracketing assumption is necessary to recover discount rates in experimental settings. Although there is an ongoing debate on whether biases are generated when hypothetical as opposed to incentivized payments are used in eliciting time preferences, numerous studies reject the presence of bias (Frederick et. al., 2002; Benhabib et. al., 2010; Pablo et al., 2020).

Table 4. 2: Money-Earlier or Later (MEL) measure of time preference (Today vs 1 year)

F3_1	**Option A**	**Choice** A	B	**Option B**
1	Receive GHC 100 **today**	○	○	Forego, GHC 75 **one year** from now
2	Receive GHC 100 **today**	○	○	Forego, GHC 110 **one year** from now
3	Receive GHC 100 **today**	○	○	Forego, GHC 120 **one year** from now
4	Receive GHC 100 **today**	○	○	Forego, GHC 130 **one year** from now
5	Receive GHC 100 **today**	○	○	Forego, GHC 140 **one year** from now
6	Receive GHC 100 **today**	○	○	Forego, GHC 150 **one year** from now
7	Receive GHC 100 **today**	○	○	Forego, GHC 160 **one year** from now
8	Receive GHC 100 **today**	○	○	Forego, GHC 170 **one year** from now
9	Receive GHC 100 **today**	○	○	Forego, GHC 180 **one year** from now
10	Receive GHC 100 **today**	○	○	Forego, GHC 200 **one year** from now

Note: We included an option where the current amount GHC 100 was larger than that for the future GHC 75 to test how attentive subjects were. In the other options, A, was fixed, while we gradually increased the amounts in B. An open-ended option was included to measure future amounts of subjects who exhausted all options provided above

Table 4. 3: Money-Earlier or Later (MEL) measure of time preference (5years vs 6 years later)

F3_4	**Option A**	**Choice** A	B	**Option B**
1	Receive GHC 100 **five years**	○	○	Forego, GHC 105 **six years** from now
2	Receive GHC 100 **five years**	○	○	Forego, GHC 110 **six years** from now
3	Receive GHC 100 **five years**	○	○	Forego, GHC 115 **six years** from now
4	Receive GHC 100 **five years**	○	○	Forego, GHC 120 **six years** from now
5	Receive GHC 100 **five years**	○	○	Forego, GHC 125 **six years** from now
6	Receive GHC 100 **five years**	○	○	Forego, GHC 130 **six years** from now
7	Receive GHC 100 **five years**	○	○	Forego, GHC 135 **six years** from now
8	Receive GHC 100 **five years**	○	○	Forego, GHC 140 **six years** from now
9	Receive GHC 100 **five years**	○	○	Forego, GHC 145 **six years** from now
10	Receive GHC 100 **five years**	○	○	Forego, GHC 150 **six years** from now

Notes: This table presents the elicitation for determining long-run time preference measures. Amounts in option A are fixed, and those in option B are gradually increased. An open-ended option was included to measure future amounts of subjects who exhausted all options provided above.

Two sets of time-dated hypothetical monetary payments, with a smaller sooner amount and a higher deferred one were presented to farmers. Tables 4.2 and 4.3 present these monetary options. In Table 4.2, for example, farmers were presented with the option of choosing GHC 100 today, and a GHC 110 in a year's time[12]. This amount in the future was increased if the farmer opted for the GHC 100 today. The procedure continued until the farmer chose an option in the future (i.e. 1 year). Thus, the parameter of interest is the point at which the farmer switches to choosing the later payment over the earlier (Dean and Sautmann, 2021). In Table 4.3, however, farmers were presented with monetary options in five and six years, with the intention to measure the time-consistency preferences. Based on the choices made by the farmers, an indifference point is inferred from the future amount just before the farmer's

[12] This approach was adopted to cleanly isolate the effect of pure time preferences from risk preferences. As pointed out by Andreoni and Sprenger (2012) when the sooner option is not received immediately but must be delayed, then the elicited time preferences is susceptible to risks because they are intricately related.

choice, and the amount chosen. Farmers' choices, thus yielded $\{y_0, t_0\}$ and $\{y_1, t_1\}$, where y_i and t_i represent the amounts and time periods, with $t_1 > t_0$.Based on the value of the future amounts that rendered farmers indifferent between current and the future amounts, we computed the required rate of return (RRR), given by the natural log of the ratio of the future and present amounts. Given the time differences, and the RRR, we computed the annualized discount rates by using the hyperbolic discounting[13] formula.

4.5 Empirical results

This section presents and discusses estimates of our empirical results. Estimates are presented under two main sub-headings. First, we present and discuss results of the drivers of rate of time preferences, and then the estimates of the results of the farmers' preferences for crop insurance program.

4.5.1 Drivers of time preferences

We estimate two sets of models; the classical linear regression and a quantile regression to account for the potential heterogeneity along the distribution of the time preference parameters. Table 4.5 presents the estimates of the drivers of time preferences. Estimates are presented in three main columns. Column 1 presents the OLS estimates of the drivers of short-run impatience measure, RTPBETA , while column 2 presents those of the long-run patience, RTPDELTA . Columns 3-5 of Table 4.4 present results of the quantile regression. Our results in column 1 show that farmers' self-assessed health status have significant impact on the rate of time preference. In particular, the estimated coefficients of the variable representing health status are negative and statistically significant in the short-run specification, suggesting that

[13] The hyperbolic discounting rate is given by $(m(0) - m(1))/m(0)$ for short-run and $(m(t) - m(t+1))/m(t)$ for the long-run.

healthy farmers are more patient compared to their unhealthy counterparts. That is, healthy and somewhat healthy farmers would have to be compensated less to defer their current

Table 4. 4: Drivers of farmers' time preferences

Variable	OLS estimates		Quantile regression		
	Short-term impatience (RTPBETA)	Long-run patience (RTPDELTA)	Short-term impatience (RTPBETA)		
			Q25	Q50	Q75
Female	-0.0127	0.0249	-0.0109	-0.0008	3.41e-16
	(0.0078)	(0.0189)	(0.0129)	(0.0117)	(0.0129)
Read & Write	-0. 0123*	-0.0207	-0.0143	-0.0047	1.12e-16
	(0.0067)	(0.0163)	(0.0101)	(0.0112)	(0.0092)
Age	0.0003	0.0045	-0.0004	-0.0006	1.89e-17
	(0.0026)	(0.0064)	(0.0036)	(0.0026)	0.0023
Healthy	-0.0427***	0.0191	-0.0452**	-0.0691***	-0.0413
	(0.0129)	(0.0314)	(0.0206)	(0.0270)	(0.0316)
S_healthy	-0.0418***	0.0105	-0.0568***	-0.0677**	-0.0413
	(0.0137)	(0.0330)	(0.0221)	(0.0274)	(0.0321)
Income/1000	-0.0006**	-0.0002	-0.0008***	-0.0007*	-2.95e-17
	(0.0002)	(0.0006)	(0.0003)	(0.0004)	(0.0004)
Heavy_alcohol	0.0529***	0.0873**	0.0346	0.0853***	0.0867***
	(0.0148)	(0.0358)	(0.0386)	(0.0328)	(0.0141)
Light_alcohol	0.0199**	0.0466**	0.0159	0.0055	1.57e-15
	(0.0088)	(0.0213)	(0.0123)	(0.0185)	(0.0207)
Occn_alcohol	-0.0122	0.0149	-0.0131	-0.0318*	-3.17e-16
	(0.0116)	(0.0280)	(0.0103)	(0.0177)	(0.0279)
Mining_town	0.0128*	-0.0152	0.0184	0.0044	-3.24e-16
	(0.0076)	(0.0184)	(0.0137)	(0.0118)	(0.0085)
Constant	0.8696 ***	0.5452***	0.8036***	0.8927***	.9302326
	(0.0197)	(0.0477)	(0.0258)	(0.0288)	(0.0336)

Notes: The table presents estimates of the factors that drive time preference parameters. Column (1) presents estimates of the drivers of the short-run discount rate, and the estimates of the drivers of the long-run are in column (2). In coulumns 3-5, estimates of the quantile regression that accounts for heteregeneity in the short-run discount rates are presented. *, ** and *** respectively denote significance at 10, 5 and 1 per cent.

consumption desires for the future. Chao *et. al.* (2009) reported similar findings on a sample of Southern African dwellers. These results are quite intuitive, given that if farmers perceive their health conditions to be bad, then the tendency for such farmers to live into the foreseeable

future to consume would be in serious doubts, hence their predisposition to be more present-biased.

Heavy alcohol consumption has positive and significant effect on time preferences. Farmers who heavily consume alcohol tend to be more myopic, presupposing that activities with short-term gratification, but potentially long-term negative consequences are more appealing to them compared to their counterparts who reported not consuming alcohol (Ferguson, 2006; Kossova et al., 2017). Similarly, the signs of the variables representing alcohol consumption reveal interesting insights on time preferences. Specifically, the estimates show positive and statistically significant impact of light alcohol consumption relative to non- alcohol consumption. However, the magnitude of the influence of heavy alcohol consumption appears to be much higher compared to the light alcohol consumption.

Residing in communities where artisanal gold mining relative to non-mining communities has positive and statistically significant impact on short-run discount rates. Activities of artisanal miners appear to have spillover effects on the value farmers place on the future. Even though farmers may not be directly involved in the artisanal gold mining activities in their villages, their mere presence appears to influence their measure of patience. This is a finding that could have implications on farming activities. For example, farmers may be more interested in less environmentally friendly farming practices that may generate substantial short-run gains, but with potentially harmful long-term environmental impacts.

The results also show that the coefficient of the variable representing gender of the household is negative, albeit, not statistically significant, but suggesting that being a female appears to be associated with lower discount rates. These findings, though not statistically significant, concurs with findings by Dittrich and Leipold (2014) who found females to be more patient on a sample of German subjects. As expected, we find higher income levels to be

negatively related to short-run measure of time preferences, indicating that the increasing incomes tend to result in a decline in rate of time preferences (Carvalho et. al., 2016). This, perhaps, may be attributed to the scarcity cognitive bandwidth proposed to be associated with poverty (Mullainathan and Shafir, 2013). The poor have most of their cognitive bandwidth pre-occupied with the scarce resources that could influence their desires for instant gratification attitudes. The levels of formal education, which we measured by the farmer's ability to read and write is found to be negatively related to time preferences, implying that more educated people tend to be more patient on the average (Perez-Arce, 2017). These findings appear to give credence to Becker and Mulligan (1997) proposition that schooling focuses students' attention on the future by communicating images of future adulthood live.

With the exception of the variables representing the levels of alcohol consumption that we find to be significantly related to our measure of long-run patience, none of the other control variables are statistically different from zero. The findings indicate that with the exception of the variables representing the level of alcohol consumption that drives long-run patience, heterogeneity in the other controls do not appear to be significantly influence our long-run patience measure. To summarize, while we found farmers who could read and write, high incomes, and better health statuses to be patient, the presence of artisanal gold mining, high alcohol consumption tend to increase impatient attitudes.

4.5.2 Heterogeneous preferences for attributes of crop insurance

We first present the estimates of the random parameter model for attributes of the insurance product alone in Table 4.5, and then that interacted with discount rates in Table 4.7, so as to integrate them into the farmers' utility. From Table 4.5, the estimates of the standard deviation of nearly all attributes are significantly different from zero, indicating the presence of preference heterogeneity. Similarly, all estimates of the mean are significantly different from

zero at 1% level, clearly indicating that the observed magnitude and sign of effects are not due to chance. The coefficient of the variable representing premium is negative, meaning farmers are sensitive to the price of the insurance product. On the level of critical yield that triggers payment, farmers have preferences for lower levels of critical yield. These findings are quite intuitive given that farmers would only be paid an indemnity based on this threshold yield. As expected, farmers have positive preferences for higher coverage. The estimates also reveal positive preferences for payments at harvesting, but negative preferences for payment at planting period. Perhaps the level of farmers' time preferences could be driving this observation. We therefore explored this mechanism, by interacting time preferences with some attributes in Table 4.6.

Table 4. 5: Random parameter model of only attributes of choice model

Variable	Mean	Standard Deviation.
κ_{Premium}	-1.1252***	1.7705***
	(0.0479)	(0.1651)
$\kappa_{\text{CriticalYield}}$	-2.0028 ***	0.3327***
	(0.0369)	(0.0319)
κ_{Coverage}	0.7132***	0.6536***
	(0.0466)	(0.0482)
$\kappa_{\text{Government}}$	0.4001***	0.3612***
	(0.0250)	(0.0391)
$\kappa_{\text{P rivate}}$	-0.1064***	0.3253***
	(0.0281)	(0.0299)
κ_{LBCs}	-0.0146***	0.2963***
	(0.0306)	(0.0319)
$\kappa_{\text{Harvesting}}$	0.0682***	0.4368***
	(0.0370)	(0.0306)
κ_{Planting}	-0.2046***	0.3173***
	(0.0327)	(0.0297)
constant	-0.2105	
	(0.0069)	
BIC	10,230.47	
AIC	10,156.56	
No. of households	750	

Notes: This table presents estimates of the random parameter model of the attributes of the insurance product. Estimates of the means of the attributes are presented in column 1, and the standard deviations that capture preference heterogeneity are in column 2. *, **, and *** respectively denote significance at 10%, 5% and 1%. Standard errors are in parentheses.

Table 4. 6: Random parameter model with attributes interacted with rate of time preference

Variable	Mean	Standard Deviation.	Mean	Standard Deviation	Mean	Standard Deviation.
κ_{Planting} * RTPBETA	-1.3681***	0.6258***			-0.0581*	0.3331***
	(0.0373)	(0.0527)			(0.0301)	(0.0285)
κ_{Planting} * RTPDELTA	-0.6103***	0.2984***			-0.0047	0.2661***
	(0.0258)	(0.0185)			(0.0234)	(0.0200)
κ_{Harvest} * RTPBETA			-1.4242***	0.6266***	-1.4096***	0.4063***
			(0.0358)	(0.0497)	(0.0328)	(0.0333)
κ_{Harvest} * RTPDELTA			0.6252***	0.3332***	0.6145***	0.2213***
			(0.0291)	(0.0249)	(0.0244)	(0.0236)
κ_{Premium}	-0.6435***	0.7496***	-0.6176***	0.6645***	-0.6351***	0.4653***
	(0.0385)	(0.0482)	(0.0326)	(0.0761)	(0.0316)	(0.0306)
$\kappa_{\text{CriticalYield}}$	-1.8499***	0.2068***	-1.8852***	0.2385***	1.9393***	0.1928***
	(0.0235)	(0.0154)	(0.0237)	(0.0292)	(0.0204)	(0.0171)
κ_{Coverage}	0.8755***	0.3220***	0.8259***	0.2918***	0.8273***	0.2470***
	(0.0305)	(0.0271)	(0.0237)	(0.0238)	(0.0256)	(0.0349)
$\kappa_{\text{Government}}$	0.4746***	0.2353***	0.4207***	0.2659***	0.4321***	0.2192***
	(0.0235)	(0.0238)	(0.0257)	(0.0223)	(0.0211)	(0.0219)
κ_{Private}	-0.1132***	0.2304***	-0.0515	0.1588***	-0.0139	0.1687***
	(0.0234)	(0.0228)	(0.0276)	(0.0179)	(0.0182)	(0.0235)

κ_{LBCs}	-0.0649***	0.2253***	-0.0590**	0.1939***	-0.0564***	0.1878***
	(0.0258)	(0.0153)	(0.0258)	(0.0142)	(0.0190)	(0.0194)
$\kappa_{\text{Harvesting}}$	0.0703**	0.3314***	0.0515*	0.2945***	0.0506**	0.2565***
	(0.0304)	(0.0237)	(0.0316)	(0.0198)	(0.0220)	(0.0289)
κ_{Planting}	-0.0696***	0.2141***	-0.0141	0.1619***	-0.0695***	0.1612***
	(0.0204)	(0.0158)	(0.0208)	(0.0174)	(0.0204)	(0.0230)
constant	-0.07317***		-0.3004***		-0.1072***	
	(0.0186)		(0.0059)		(0.0088)	
No. of Households			750			

Notes: The Bayesian estimation procedure was used to avoid the challenge of non-convergence that may be associated with the classical method. While the first two columns contain estimates of the insurance attributes, and the interaction of time preference parameters and *Planting* attribute, the third and fourth columns contain estimates of all attributes, as well as the interactions of time preferences and *Harvesting*. The last two columns contain interactions of time preference parameters with *Planting* and *Harvesting* attributes. *, ** and *** respectively denote statistical significance at 10%, 5% and 1%. Standard errors are in parentheses.

We explored the heterogeneous impacts of discount rates on attributes of the crop insurance program in Table 4.6. Our results show a significant and negative effect when short-run discount rates is interacted with the variable representing harvest. These findings are not surprising, given that an impatient farmer prefers to receive benefits immediately. However, in terms of cost, these individuals would prefer to defer that to a later date (Cohen et al., 2020). Similarly, our findings show a negative relationship between the rate of time preferences and the planting crop insurance attribute. These findings are not surprising, given that farmers facing liquidity constraints may exhibit disutility towards paying insurance premiums during the planting season. The signs of the effects of all other attributes of the insurance products are similar to those without the interaction terms (see Table 4.5).

Estimates of a more comprehensive specification of the Hybrid model are presented in Table 4.7. Given that farmers' choice of crop insurance attributes may be driven by some underlying latent constructs, we jointly modelled these constructs with choice of insurance products' attributes. In particular, we estimate crop insurance choice with farmers' socioeconomic characteristics, their attitudes and perceptions towards yield risks and insurance, and accounting for their stated ANA of the respondents. All the attitudinal variables included in the model are statistically different from zero at conventional levels, suggesting that these latent variables play relevant roles in informing the underlying utility farmers derive from the insurance product. In particular, farmers who either strongly agreed or agreed to obtaining lower yield compared to the average farmer in their community, those with higher yield variability and expect their yields to decrease in the near future tend to exhibit positive utility to the cocoa insurance product. However, cocoa farmers who disagreed that cocoa crop insurance will be relevant in the future and not now, and that government would come to their aid in the event negative outcomes, had significant and positive utility.

Table 8: Hybrid model estimates of farmers' preferences for insurance attributes

Respondents	750		
Observations	8,250		
Final loglikelihood	–19,379.18		
AIC	38,842.35		
BIC	39,036.40		
Variable	Coefficient	Standard errors	t - statistic
Structural equations (behavioral variables)			
$\vartheta_{\text{RTPBETA}}$	-0.4270***	0.0853	-5.01
$\vartheta_{\text{RTPDELTA}}$	0.0326	0.0589	0.55
$\vartheta_{\text{Lossaversion}}$	0.0338**	0.0139	2.42
$\vartheta_{\text{Riskaverse}}$	0.1340***	0.0307	4.35
Structural equations (socioeconomic variables)			
$\vartheta_{\text{Female}}$	-0.2260***	0.0396	-5.70
$\vartheta_{\text{Readwrite}}$	0.1090***	0.0274	3.98
$\vartheta_{\text{LiqConstraint}}$	-0.0796***	0.0276	-2.89
$\vartheta_{\text{Coshar100}}$	0.0529**	0.0250	2.12
Measurement equations (attributes of choice)			
κ_{Coverage}	0.7570***	0.0946	8.00
$\kappa_{\text{CriticalYield}}$	-1.9400***	0.1290	-15.00
$\kappa_{\text{Government}}$	1.5200***	0.1280	11.80
κ_{Private}	1.0400***	0.1250	8.33
κ_{LBCs}	-0.1190**	0.0500	-9.06
$\kappa_{\text{Harvesting}}$	1.1200***	0.1450	7.69
κ_{Planting}	-0.1900***	0.0481	-3.96
κ_{Premium}	-0.7660***	0.1140	-6.74
Measurement equations (latent variable – attitude towards yield risks and insurance)			
τ_{YCIP1}	0.6700***	0.2430	2.76
τ_{YCIP2}	0.4000**	0.1990	2.01
τ_{YCIP3}	0.3930**	0.1730	2.27
τ_{YCIP4}	-0.3970*	0.2060	-1.93
Measurement equations (latent variable – attribute-non-attendance)			
$\psi_{\text{CoverageANA}}$	1.5900***	0.3380	4.70
$\psi_{\text{CriticalYieldANA}}$	1.9800***	0.4750	4.18
$\psi_{\text{ManagementANA}}$	1.8200***	0.4130	4.42
$\psi_{\text{PeriodANA}}$	0.4730***	0.3750	5.98
Constant	-0.5900***	0.0420	-14.10

Note: This table shows the estimation results of the hybrid choice model that incorporates farmers' attitudes and perception about insurance, and farmers reported attribute non-attendance. The joint estimation addresses any potential endogeneity problems. ***, ** and * respectively denote significance at 1%, 5% and 10% .

The variable representing short-run discount rates exert negative and statistically significant impact on utility farmers derive from crop insurance, suggesting that farmers who are less patient in the short-run tend to derive disutility from crop insurance uptake. Given that any potential indemnity payments are received later in the event that the insurance triggers payments, the delay serves as a disincentive to the present-biased farmers (O'Donoghue and Rabin 1999; Laibson 2015). On the contribution of the long-run discount rate measure on the underlying utility for cocoa insurance, the results indicate a positive relationship. These results concur with our previous estimates in Table 4.5, where we ignored a number of underlying structures of farmers' utility on cocoa insurance decisions. The findings appear to show clear evidence of time inconsistency, where farmers tend to be impatient in the short-run prospects, but patient in the long-run. These findings show that if farmers are naïve of the time inconsistencies in their insurance uptake decisions, they may renege on their payment commitment during harvest. The level of loss aversion, positively impact utility on cocoa insurance, clearly indicating that cocoa farmers who are more averse to loses relative to equivalent gains derive positive utility from crop insurance participation.

As shown in Table 4.7, the estimates show that farmers have positive and significant utility towards higher levels of insurance coverage, insurance managed by either government or private companies and products with delayed payments until harvesting. However, there is significant disutility on higher levels of critical yields, insurance product managed by an LBC, and the cost of the insurance product, premium. Clearly, these estimates appear rational from the farmer's perspective. Given that insurance is a normal good, higher premiums result in low demand by farmers. Similarly, higher critical levels imply lower likelihood of being paid an indemnity, hence their disutility towards higher critical levels. The rather negative preference for licensed buying companies (LBCs) appear to have a long political economy antecedent. Prior to the introduction of LBCs in 1993 in Ghana, local intermediaries mediated the

marketing of cocoa beans between the foreign merchants and farmers. Following cocoa farmers' holdout of the produce from foreign merchants after announcing market-sharing arrangement, these intermediaries were blamed for simultaneously extracting rent from growers and exporters in the Nowell Commission report. Perhaps farmers' current actions may be driven by their previous experiences with LBCs, where each partner views one another as behaving opportunistically.

Interestingly, the estimates in Table 4.4 show that even though farmers are time-inconsistent in discount rates, yet, they appear to have positive preference for paying for the insurance product after harvesting. Given that farmers generally prefer payments at harvesting periods relative to planting, perhaps the price of the insurance premium, relative to farmers' incomes at the time of harvesting may appear small, and hence could be driving their preferences (Azar, 2007; Tversky and Kahneman, 1981). From a policy perspective, this has two implications. If farmers are aware that they are time-inconsistent, they would naturally demand for commitment device to minimize their options in fulfilling their future repayments. By demanding for commitment device, they tend to reduce the available options in the future because of the tendency for them to renege on their earlier decisions. Under this scenario, the sustainability of the insurance product would not be put into question. However, if cocoa farmers are naïve of their time inconsistency, even though they have positive utility for delaying payments until harvesting, they may not follow through with their promise. This would have serious consequences on the sustainability of the insurance product.

4.6 Conclusion

One of the widely documented puzzles in the empirical literature is the co-existence of evidence of risk aversion among farmers from developing countries, and very low uptake of agricultural insurance when offered the opportunity to do so. It has been argued in recent times

that agricultural insurance does not only transfer incomes from a good to a bad state, but also incomes are transferred across time. This presupposes that risk-aversion may be necessary but not sufficient to stimulate the uptake of agricultural insurance. Hence, rate of time preferences may be mediating the insurance uptake decisions. In this paper, we examined the main drivers of rates of time preferences in a developing country context, and investigated the relationship between rate of time preferences and preferences for attributes of a heterogeneous ideal area-yield insurance product.

Given the lack of crop insurance products in Ghana, we used discrete choice experiment to design the ideal area yield insurance product with attributes including coverage, critical yield, period of payment, management of the product, and premium. Using a series of multiple price list (MPL) approach, we measured farmers' rate of time preference using the money-earlier or later method. Simple linear regressions and quantile regressions to account for heterogeneity in time preferences were employed to examine the drivers of rate of time preferences. We then estimated the discrete choice model with a mixed logit and the hybrid models, accounting for the attribute processing strategies for the respondents.

The empirical results showed that farmers' discount rates are characterized by intrapersonal commitment inconsistencies, exhibiting impatience in the short-run. We also found that literacy level, household incomes and subjective assessment of health status are the main drivers of time preferences. In addition, our results show that farmers residing in communities with artisanal mining activities tend to be less patient. This could have serious implications on farmers' tendencies to pay for the insurance, given that the most preferred period of payment was at the harvest. Other attributes that farmers tend to derive positive utility include higher levels of coverage, government or private managed insurance products.

However, farmers appear to derive disutility from insurance products managed by licensed buying companies, higher critical yields and premiums.

These findings have implications in the design of crop insurance products. In particular, crop insurance uptake could be enhanced by allowing farmers to make payments during harvesting. However, effective policies need to be instituted to address the potential of non-payments of premium, given that farmers appear to exhibit time-inconsistencies in their measured time preferences. Remedial measures such as commitment devices could be employed to nudge farmers to honor their promises during repayment of the insurance products.

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4.8 Appendices

Appendix A: Robustness check using inferred attribute non-attendance

Using the Equality-constrained latent model, we are able to infer the probability of farmers non-attendance to a sub-set of the attributes of the insurance product. This is achieved by restricting the utility coefficient by specifying some classes with their parameters restricted to zero (Goncalves et al., 2020). Table A1 presents the proportion of farmers who did not attend to attributes.

Table 4.A1: Attribute non-attendance based on Equality-constrained latent class model (ECLC)

Class description	Proportion	Percentage
Full attendance	0.001	0.1%
Ignored only:		
Critical Yield	0.034	3.4%
Coverage	0.000	0%
Management	0.552	55.5%
Payment Period	0.009	0.9%
Premium	0.305	30.5%
Full-non-attendance	0.099	9.9%

Notes: This table presents the proportion of non-attendance to the attributes of the insurance product. Each of the five attributes were constrained in turns to and compared to the unconstrained version of the model to generate the proportion of respondents who did not attend to the attributes. Two other specifications, one with full attendance and the other with non-attendance to any of the attributes.

The results reveal that only about 0.1% of farmers did not attend to all the attributes of the insurance product, implying that a substantial proportion of farmers paid particular attention to all attributes. Our results further reveal that only 0.9% of farmers did not attend to the period the insurance premium has to be paid. These findings are quite important because more than 99% of the time, farmers considered this attribute in their choice of the insurance product. Given that the period of payment of premium is relevant in increasing crop insurance uptake decisions (Casaburi and Willis 2018), farmers paying particular attention to this attribute

implies its non-triviality in their insurance uptake decisions. Also, in as much as the premiums of the insurance product are relevant, our results reveal that farmers paid comparatively more attention to the period of insurance payment (99%) compared to the costs of the insurance (70%). This further underscores the recent recommendation by scholars in delaying the period insurance premiums are paid to increase uptake (Casaburi and Willis 2018; Belissa et al. 2019)

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Table 4. 7A**:** Variable description and summary statistics

Variables	Variable description	Mean	S.D
Panel A: *Behavioral variables*			
RTPBETA	Rate of time preference (MEL) for short run impatience	0.82	0.09
RTPDELTA	Rate of time preference for long run patience	0.59	0.22
Lossaversion	Value of loss aversion	3.24	1.49
Riskaverse	Self-reported risk-aversion. 1 if farmer is risk averse, 0 otherwise	0.63	0.48
Panel B: *Attributes of the insurance product*			
Coverage	Proportion of average yield covered by the insurance	0.34	0.29
CriticalYield	Critical yield that triggers indemnity payment (64 kg Bag /10)	0.29	0.25
Govt	1 if the insurance is government managed, 0 otherwise	0.43	0.47
LBC	1 if the insurance is licensed buying company managed, 0 otherwise	0.31	0.46
Private	1 if the insurance is private firm managed, 0 otherwise	0.23	0.42
Harvesting	1 if payment is made at harvest period, 0 otherwise	0.38	0.48
Planting	1 if payment is made at the beginning of the planting period, 0 otherwise	0.29	0.45
Premium	Cost of insurance per acre (GHC'00/acre)	0.81	0.59
Panel C: *Health status and health behavior*			
Healthy	Self-reported measure of health, 1 if healthy, 0 otherwise	0.64	0.48
Somehow_healthy	Self-reported measure of health, 1 if somehow healthy, 0 Otherwise.	0.29	0.45
Unhealthy	Self-reported measure of health, 1 if unhealthy, 0 otherwise	0.07	0.26
Heavy_alcohol	1 if farmer reports as heavy alcohol consumer, 0 otherwise	0.05	0.23
Light_alcohol	1 if farmer reports as light alcohol consumer, 0 otherwise	0.17	0.23
Occn_alcohol	1 if farmer reports as occasional alcohol consumer, 0 Otherwise.	0.09	0.29
No_alcohol	1 if farmer reports as non-alcohol consumer, 0 otherwise	0.69	0.46
Panel D: *Socio-economic characteristics*			
Female	1 if female, 0 otherwise	0.25	0.44
Read & write	1 if farmer can read and write in English, 0 otherwise	0.47	0.50
Age	Age of household head (years)	52.06	12.59

Liquidity constraints	1 if farmer is liquidity constrained, 0 otherwise	0.35	0.47
Income/1000	Total annual income in GHC '1000	12.35	13.43
Coshare100	1 if income from cocoa makes up 100% of total household income distribution, 0 otherwise	0.50	0.50
Mining_town	1 if farmer resides in an artisanal gold mining town, 0 otherwise.	0.24	0.43

Notes: This table presents the descriptive statistics of the variables used for our estimations. S.D denotes standard deviation

Table 4. 8A: Elicitation of loss aversion

F3_1	Option A		Choice		Option B	
			A	B		
1	***Gain*** GHC 20	***Lose*** GHC 9	○	○	***Gain*** GHC 50	***Lose*** GHC 43
2	***Gain*** GHC15	***Lose*** GHC 9	○	○	***Gain*** GHC 50	***Lose*** GHC 43
3	***Gain*** GHC 9	***Lose*** GHC 9	○	○	***Gain*** GHC 50	***Lose*** GHC 43
4	***Gain*** GHC 5	***Lose*** GHC 10	○	○	***Gain*** GHC 50	***Lose*** GHC 43
5	***Gain*** GHC 5	***Lose*** GHC 10	○	○	***Gain*** GHC 50	***Lose*** GHC 43
6	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
7	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
8	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
9	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
10	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43

Table 4. 9A: Attributes and levels of the insurance product

Items	Description	Level 1	Level 2	Level 3
Payment period	Period of the cocoa season when insurance product is sold	Planting	Harvesting	
Management	The seller and manager of the insurance product	Government	Licensed buying Companies (LBC)	Private insurance company
Coverage	Percentage of the average area yield that is insured.	25%	50%	75%
Critical yield	The threshold yield below which the insurance triggers payment (kg per Ha)	194	291	388
Premium	The cost of the insurance product (GHC/acre) of matured cocoa trees	100	120	150

Table 4. 10A: A sample of choice set

Product characteristics	***Insurance X***	***Insurance Y***	
Critical yield			
Coverage	75%	50%	
Management	Government	Private	***No Buy***
Payment period	Planting	Harvesting	
Premium	GHC 150	GHC 100	
I will choose …	☐	☐	☐

Chapter Five

The impact of informal risk mitigation measures on input use and welfare: Evidence from rotating savings and credit associations (ROSCAS) in Ghana

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Abstract

The role of informal financial institutions, such as rotating savings and credit associations (ROSCAS) in addressing aggregate shocks to increase investments remains debatable in the literature till date. Using recent data from Ghana, we investigate the impact of ROSCAS on investments in farm inputs and incomes, by applying the marginal treatment effect (MTE) framework that simultaneously accounts for selection bias and heterogeneity across farming households. The empirical results reveal that farmers with high propensity to participate in ROSCAS invest more in farm inputs and earn significantly higher farm incomes compared to non-participants. In particular, non-participating farmers who experienced higher aggregate shocks decrease investments in farm inputs, and earn significantly less farm incomes. However, for ROSCAS participants, experiencing high incidence of shocks significantly increase investments in these inputs, and they earn higher farm incomes. These findings have implications on policy in that these informal institutions can play crucial role in the interim while efforts are made to increase uptake of formal insurance.

Keywords: aggregate shocks, rotating savings and credit association (ROSCAS), marginal treatment effect (MTE), informal financial institutions

JEL Codes: C36, D02, E26, G52, O17

1.0 Introduction

Addressing risk-induced poverty is crucial to improving the welfare of rural poor, given their disproportionately huge dependence on extremely volatile agriculture (Dercon and Christiaensen 2011; Hansen et al., 2022). These exposures are much more severe among perennial tree crop farmers who have to cope with substantial time gap between input purchases and output in their production. Ideally, the rural poor are expected to resort to financial and insurance to help cope with the negative effects of these risk exposures. Unfortunately, the characteristic imperfect rural financial markets often make it prohibitively expensive in making formal financial services available. Even under conditions where these formal financial services have been piloted, uptake have been disappointingly low (Takahashi et al, 2016; Ali et al., 2020). In the absence of these formal financial markets, informal institutions such as rotating, savings and credit associations (ROSCAS) tend to play an important role (Dupas and Robinson 2013; Aggarwal et al., 2018; Sedai et al. 2021).

ROSCAS are a group of individuals who have voluntarily agreed to contribute, mostly financially, at regular interval towards a pool, which is subsequently allotted on a random basis, through bidding or other[14] means agreed in advance (Calomiris and Rajaraman 1998; Kan 2000). The contribution and disbursement of the funds continue until the last member receives her share. Afterwards, the group may be disbanded or commence a new cycle. ROSCAS, unlike other informal groups, drive economic welfare in a unique and intriguing manner (Ibrahim 2019; Klonner 2003; Dekle and Hamada 2000).

First, unlike autarkic savings that the individuals have to save for considerably long period, ROSCAS provide intertemporal gains by mobilizing resources from the group to enable some members acquire indivisible goods sooner (Besley et al., 1993; Bonan et al., 2019).

[14] Other basis for allotting pooled funds include consensus among members, hierarchy in terms of time members joined ROSCAS, and discretion of the group leader.

Second, ROSCAS serve as commitment devices to improve savings, particularly among individuals with difficulty in following through with their intentions by discouraging their future selves from reneging (Rabie 2021; Bonan et al., 2019; Basu 2011; Ambec and Treich 2007). Third, by treating funds meant for the association differently, members of ROSCAS are capable of increasing their savings and subsequent investments in indivisible goods (Aggarwal et al., 2018).

Although some authors have reported of ROSCAS playing a crucial role of risk-sharing as a means of mitigating risks, *albeit* incomplete (Etang et al., 2011; Calomiris and Rajaraman 1998), the evidence have been mixed and inconclusive. The lack of consensus has sparked a renewed interest in recent times in gaining insights into their risk mitigation roles (Baland et al., 2019; Klonner 2008). Klonner (2008), for example, point out that members of ROSCAS tend to mitigate individual-specific risks and uncertainties which could have consequences on their investment behavior. However, as widely acknowledged by numerous studies, their role under aggregate shocks remains hotly debatable (Gallagher and Hartley, 2017; Czura and Klonner 2018).

The economic literature is replete with empirical evidence of risks and uncertainties constraining farmers' investment decisions in profitable farm inputs (Karlan et al., 2014; Cai 2016). However, when farmers are offered agricultural insurance in an attempt to address these risks and uncertainties, uptake has been surprisingly low (Karlan et al., 2014; Jensen et al., 2017; Ali et al. 2020), raising questions of their suitability to smallholder farmers. Farmers' lack of understanding of the workings of these formal agricultural insurance products has been cited as a major constraint to their uptake decisions (Takahashi et al., 2016; Cai and Song 2017). Unlike the novel formal insurance that most rural poor lack understanding of, ROSCAS have been in existence in most developing countries for centuries (Kan 2000; Bonan et al.,

2019). This study aims to investigate the impact of participation in ROSCAS on farmer's investment decisions in farm inputs and welfare under varying risks conditions.

Previous studies have largely focused on the impacts of ROSCAS participation on outcomes such as household incomes and expenditures (Brunie et al. 2017; Sedai et al., 2021; Lensink et al 2015), assets accumulation (Handa and Kirton 1999) and fertility choice among women (Sedai et al., 2021). A large strand of the literature on the other hand has focused on the drivers of participation in ROSCAS (Rabie 2021; Alhassan et al., 2019; Anderson and Baland 2002). While there appears to be a growing body of evidence on the drivers of ROSCAS participation and their impacts on incomes (Rabie 2021; Alhassan et al., 2019; Brunie et al., (2017), there is paucity of evidence on their impacts on farm input use. Understanding the impacts of participation in ROSCAS on investments in farm inputs is crucial because the low application of farm inputs has been recognized as one of the major constraints to improving productivity, and holds the greatest potential in spurring the needed economic transformation in sub-Saharan Africa (Jayne et al., 2019; Adjognon et al., 2017; Sheahan and Barrett, 2017).

Our study therefore makes the following contributions to the literature: First, this study examines the impacts of ROSCAS on investments in farm inputs under both aggregate and idiosyncratic risks. To date, previous studies have reported their impacts under idiosyncratic risks, (Klonner 2003; Klonner 2008; Baland et al., 2019). Although these studies provide some insights, it is more comprehensive to understand the role of ROSCAS under aggregate risks, given the long-held skepticism regarding their impacts (Townsend 1995; Gallagher and Hartley, 2017; Czura and Klonner 2018). This, will thus provide broader perspective into how ROSCAS influence investment decisions and welfare in a comprehensive risk environment.

Second, this study contributes methodologically by examining the heterogeneity in gains to participating in ROSCAS. Besley et al. (1994) proposed theoretically that the expected

utility may differ conditional on how the pooled funds are disbursed. They, however, presented no empirical evidence to validate the potential heterogeneity in benefits of joining ROSCAS. We address this by estimating the marginal treatment effect (MTE) model that accounts for both observed and unobserved characteristics of farmers, and more importantly allows for the benefits of participation to differ across farmers. The empirical results reveal that experiencing aggregate shocks decrease significantly investments in farm inputs, and decreased farm incomes among non-participants. However, among ROSCAS participants, experiencing aggregate shocks increases farm inputs and incomes.

The rest of the paper proceeds as follows: In section 2.0 we present the theoretical model; Section 3.0 outlines the empirical identification strategy. While section 5.3 presents the data collection process, sections 5.4 to 5.6 present the descriptive and empirical results. Section 5.7 presents the conclusion of the study.

2.0 The model

In this section, we argue that ROSCAS provide insurance, *albeit* imperfect, to increase investments in indivisible farm inputs and household welfare. Our model relies largely on the studies by Besley et al., (1993;1994), and Baland et al., (2019). We consider a group of cocoa farmers who each earn income y, subject to shocks such as disease outbreaks, dry-spells, etc. Shocks occur with a probability σ, and in situations without shocks, $(1-\sigma)$. In times of shocks, the farmer's income decreases by an amount, s, such that incomes at period of shock is $\underline{y} = y - s$, implying $\underline{y} < y$. It is further assumed that the production function that generates the utility for household consumption comprises divisible inputs, d, such as seeds, and indivisible inputs, i, such as motorized sprayer and labor. The farmer's utility, u, assumed to be twice differentiable, can be expressed as $u(\bar{i}, d)$, if she owns an indivisible input, and $u(\underline{i}, d)$ otherwise. We characterize the farmer's discount factor, θ, as $0 < \theta < 1$. Possessing

the indivisible input increases productivity, so that the gains in utility can be expressed as: $u(\bar{i},d) \geq u(\underline{i},d)$.

To simplify our analysis, we assume two members, farmer 1 and farmer 2, participating in a two-period ROSCAS, $t = 1 \,\&\, 2$. As stated above, there exist productive gains, if the farmer utilizes indivisible inputs, as there is an incentive to purchase the indivisible input. Assuming the indivisible input costs h, and the farmer is liquidity-constrained, she is unable to purchase the indivisible input in the first period, implying that $y < h < 2\underline{y}$. If the two farmers agree to form a ROSCA, with each contributing half the cost of the indivisible input $\left(\frac{1}{2}h\right)$, then at least one of them would gain intertemporally, through early receipt and utilization of the input. The expected utility of the first receiver of the 'pot', farmer 1, is given by:

$$EU^{R_1} = \sigma u\left(\underline{y} + \tfrac{1}{2}h\right) + (1-\sigma)u(y) + \theta\left[\sigma u\left(\underline{y} - \tfrac{1}{2}h\right) + (1-\sigma)u\left(\underline{y}\right)\right] \tag{5.1}$$

The first two terms of equation (1) represent the utilities in period 1, with the first term being utility with shocks, and the second, utility without shock. For period 2, the utilities are discounted, with the factor θ. Similarly, the expected utility of the second farmer for the two periods is given as:

$$EU^{R_2} = \sigma u\left(\underline{y} - \tfrac{1}{2}h\right) + (1-\sigma)u(y) + \theta\left[\sigma u\left(\underline{y} + \tfrac{1}{2}h\right) + (1-\sigma)u\left(y + \tfrac{1}{2}h\right)\right] \tag{5.2}$$

where σ and $(1-\sigma)$ represent probability of experiencing and not experiencing shocks, respectively; E is the expectation operator and all other variables remain as previously defined. The expected utility for a non-participant saving alone is given by:

$$EU^{N} = \sigma u\left(\underline{y}\right) + (1-\sigma)u(y) + \theta\left[\sigma u\left(\underline{y}\right) + (1-\sigma)u(y+h)\right]$$

(5.3)

Equation (5.3) suggests that a non-participant can only purchase the indivisible input at the end of the period, hence does not gain intertemporarily. Given that $\theta < 1$ the expected utility of

farmer 1 is higher than that of farmer 2, i.e. $EU^{R_1} - EU^{R_2} > 0$. However, in the case of farmer 2 and the non-participant, the expected utilities are equal $EU^{R_2} - EU^{N} = 0$. This is the case of no income or risk sharing arrangement within the ROSCAS. In conditions where risks are shared, joining ROSCAS is associated with additional benefits. Kedir and Ibrahim (2011) and Etang et al. (2011), for example, report of additional provision to support in times of emergencies such as serious illness or death to members of ROSCAS. We will first analyze the condition of uncorrelated (or idiosyncratic) risks, where only one of the farmers is hit by shocks, and then present the correlated risk condition. If farmer 2 is hit by a shock but farmer 1 is not hit in period 1, and the latter shares income with her, then farmer 2's expected utility is expressed as:

$$E\bar{U}^{R_2} = \sigma u\left(\underline{y} - \tfrac{1}{2}h\right) + (1-\sigma)u(y+k) + \theta\left[\sigma u\left(\underline{y} + \tfrac{1}{2}h\right) + (1-\sigma)u\left(y + \tfrac{1}{2}h\right)\right] \quad (5.4)$$

where k is a positive income obtained from farmer 1, and all other variables remain as previously defined. Equation (4) indicates that under shocks, the expected utility of farmer 2 is higher than non-participant, $E\bar{U}^{R_2} - EU^{N} > 0$. On the other hand, if farmer 1 is not hit by shocks, and receive income k from farmer 2, then the difference in expected utility of farmer 1 over farmer 2 becomes even larger. The analysis above has rather focused on one of the members of the ROSCAS.

Incorporating the intertemporal gains from early ownership of the indivisible inputs and the potential gains from income-sharing, the expected utility from joining ROSCAS is given as:

$$E\bar{U}^{R} = \sigma^2 u\left(\underline{y} - \tfrac{1}{2}h, \bar{i}\right) + (1-\sigma)^2 u\left(y - \tfrac{1}{2}h, \bar{i}\right) + 2\sigma(1-\sigma)u\left(\tfrac{1}{2}\left(y + \underline{y}\right) - \tfrac{1}{2}h, \bar{i}\right) \quad (5.5)$$

From equation (5.5), σ^2 depicts the joint probability of both farmers of the ROSCAS hit by a shock. Under such a condition, both farmers' incomes are expected to decrease, hence the

prospect of sharing incomes amongst them has often been met with skepticism among some economists (McKenzie 2003; De Mel et al., 2012). However, as argued in the recent literature, under covariate risks, there exists some income sharing due to the marked heterogeneity on the extent to which households are hit even in the same community (Gallagher and Hartley 2017; Czura and Klonner 2018), suggesting that farmers who suffer less can still share with their neighbors. In the case of independent probabilities of being hit by shocks $(1-\sigma)^2$ and $2\sigma(1-\sigma)$, the usual risk sharing is expected. This implies that joining ROSCAS offers some insurance, *albeit* imperfect. The expected utility of a farmer outside the ROSCAS is as:

$$E\bar{U}^N = \sigma^2 u\left(y-\tfrac{1}{2}h, \underline{i}\right) + (1-\sigma)^2 u\left(y-\tfrac{1}{2}h, \underline{i}\right) + 2\sigma(1-\sigma)u\left(\tfrac{1}{2}\left(y+\underline{y}\right)-\tfrac{1}{2}h, \underline{i}\right) \quad (5.6)$$

From equations (5) and (6), the expected utility from participating in ROSCAS is higher than not participating. This can be expressed as:

$$\begin{aligned} E\bar{U}^R - E\bar{U}^N &= \sigma^2 u\left(\underline{y}-\tfrac{1}{2}h, \bar{i}\right) + (1-\sigma)^2 u\left(y-\tfrac{1}{2}h, \bar{i}\right) + 2\sigma(1-\sigma)u\left(\tfrac{1}{2}\left(y+\underline{y}\right)-\tfrac{1}{2}h, \bar{i}\right) \\ &- \left[\sigma^2 u\left(y-\tfrac{1}{2}h, \underline{i}\right) + (1-\sigma)^2 u\left(y-\tfrac{1}{2}h, \underline{i}\right) + 2\sigma(1-\sigma)u\left(\tfrac{1}{2}\left(y+\underline{y}\right)-\tfrac{1}{2}h, \underline{i}\right)\right] > 0 \end{aligned} \quad (5.7)$$

Equation (5.7) provides the basis for our proposition.

Proposition: Farmers will invest more in farm inputs from participating in ROSCAS, under both covariate and idiosyncratic risks.

3. Conceptual framework

In this section, we present the strategy used in identifying the impact of participation in ROSCAS on a number of outcome variables, such as investments in farm inputs and farm incomes. In line with equation (5.7), we argue that farmers will participate in ROSCAS depending on the difference between the expected utilities of the two participation conditions. Thus, they weigh up the expected net utility for participation and non-participation in ROSCAS. The participation decision can then be considered as a binary choice problem that is based on the maximization of the underlying utility function. If we denote the expected utility

from participating in ROSCAS as R_{i1}^{*} and the expected utility from non-participation as R_{i0}^{*}, then the difference between the expected utilities can be specified as $R_i^{*} = R_{1i}^{*} - R_{0i}^{*}$. Given that the actual level of utility for each farmer cannot be observed, but it can be represented by the observed choice $R_i = 1$ being participation, and $R_i = 0$ as non-participation. Using the counterfactual framework, two potential outcomes: Y^R representing the outcome (i.e. farm inputs and incomes) from participation in ROSCAS, and Y^N, the outcome of the same farmer without participating are specified. The potential outcome variables, Y^R and Y^N can each be expressed as function of a vector of observable characteristics X', and unobservables ω_1 and ω_0 in the equations:

$$Y^R = \delta_1 X' + \omega_1$$
$$Y^N = \delta_0 X' + \omega_0 \tag{5.8}$$

Only one of the two potential outcomes is observable to the researcher for each farmer, implying that we can observe only the outcome of a farmer either participating in ROSCAS or not, and not both. For this reason, the counterfactual would have to be generated using an appropriate statistical approach. Given that the decision to participate in ROSCAS is not randomly assigned, our estimates could suffer from potential endogeneity problems arising from selection bias if the participation decision is treated as exogenous variable in the outcome equations. We use a set of instruments for identifying the causal impact of participation in ROSCAS. Applying the marginal treatment effect (MTE) proposed by Heckman and Vytlacil (2007) and Andresen (2018), and recently modified by Zhou and Xie (2019), the farmers' expected utility, R_i^{*}, can be expressed as a function of observable characteristics, including the set of instrumental variables G_i', and unobservable factors V_i, in equation (5.9) below

$$R_i^* = \mu G_i' - V_i, \qquad \text{where } R_i = 1\left[R_i^* \geq 0\right] = 1\left[\mu G_i' \geq V_i\right] \tag{5.9}$$

The unobserved factors V_i, interpreted as the resistance to participation in ROSCAS, is assumed to be continuously distributed. That is, farmers with high values of V_i are less likely to participate in ROSCAS relative to those with low values.

For the purposes of identification, we used the distance from the farmers' residence to the nearest formal financial institution and the level of financial concentration. As rightly pointed out by Gugerty (2007), ROSCAS tend to be found in settings with thinly or non-existent formal financial services. From a transactional economics theory, these formal financial institutions tend to concentrate in urban settings, making it prohibitively expensive for farmers who largely reside in rural areas to patronize. This implies that the further away farmers are from these formal financial institutions, the more likely the farmers would participate in ROSCAS (Gugerty 2007). The level of financial concentration, which denotes the number of formal financial institutions in the district is also used as an instrument. We argue that the higher the number of formal financial concentration in the district, the lower the likelihood will be for farmers to participate in an informal institution such as ROSCAS. As Moffitt (2009) clearly point out, this aggregate level geographical variable reflects the broader financial environment farmers operate. Given that individual farmers have no influence whatsoever on the establishment of these formal financial institutions, these variables are strong predictors of their participation but are less likely to be correlated with error term, and hence fulfil both the exogeneity and exclusivity criteria to be valid instruments.

From equation (5.9), we can transform the inequality term in $R = 1\left[\mu G' \geq V\right]$ by applying the cumulative density function (CDF) of the unobserved resistance to participation V to the linear index $\mu G'$ to obtain equation (5.10) below:

$$P(G)=P(R=1|Z)=\Phi(\mu G'),D=1\left[R^{*}\geq 0\right]=1\left[P(G)\geq \omega_D\right] \tag{5.10}$$

where $P(G)$ is the propensity score; ω_D is the quantiles of the resistance to participation V, and $\Phi(\cdot)$ is the CDF function of V used for the transformation. The marginal treatment effect framework allows for correlation between ω_0, ω_1 and ω_D, so as to derive the conditional difference in outcomes for participants and non-participants in ROSCAS as:

$$MTE(x,\varpi)\equiv E\left(Y^R-Y^N\,|X=x,\omega_D=\varpi\right)=x(\delta_1-\delta_0)+E\left(\omega_1-\omega_0|\omega_D=\varpi\right) \tag{5.11}$$

Where $x(\delta_1-\delta_0)$ represents the heterogeneity in the observable characteristics, and $E\left(\omega_1-\omega_0|\omega_D=\varpi\right)$ the heterogeneity in the unobservables. This is a clear improvement upon the Endogenous Switching Regression (ESR) model that assumes a homogeneity in the unobserved characteristics. That is, the MTE showcases the returns to participation in ROSCAS for a given farmer with observed characteristic $X=x$ and the $\omega_D=\varpi$ quantile of the unobserved V distribution (Cornelissen et al. 2018). A farmer with these observed and unobserved characteristics is described as marginal because of the indifference between participating and not participating in the ROSCAS whenever the index of the observed characteristics $\mu G'$ equals the unobservables V .Using the propensity score $P(G)$ as the local instrument, we find the derivative of the outcome variable Y, with respect to the $P(G)$, so that the expectation of Y is given as:

$$E\left(Y\,|X=x,P(G)=p\right)=x\delta_0+x(\delta_1-\delta_0)\,p+pE\left(\omega_1-\omega_0|\omega_D\leq\varpi\right) \tag{5.12}$$

The nonlinear function of the propensity score, $pE\left(\omega_1-\omega_0|\omega_D\leq p\right)$ captures the unobservable resistance to participating in ROSCAS, ω_D. The MTE is estimated by allowing $K(p)$ to

represent the non-linear function, $pE\left(\omega_1 - \omega_0 \middle| \omega_D \leq p\right)$, and taking the derivative of equation (5.12) with respect to $P(G) = p$, and evaluated at the quantiles of the unobservables $\omega_D = \varpi$ to obtain:

$$MTE(x,\omega) = \frac{\partial E\left(Y \middle| X = x, p\right)}{\partial p} = \left(\delta_1 - \delta_0\right)x + E\left(\omega_1 - \omega_0 \middle| \omega_D = \varpi\right) \tag{5.13}$$

We implement the MTE by first estimating decision equation using a probit model, taking cognizance of the exclusion restriction to obtain the propensity score $P(G) = p$. In the second-stage, we model the outcome equation semi-parametrically as a function using the second-order polynomial of the non-linear function $K(p)$. The marginal treatment effect is then obtained as the derivative of the outcome variable with respect to quantile of propensity score (Cornelissen et al., 2016). If we let $K(p) = \alpha p + \varepsilon$, equation (5.12) can be simplified to obtain (5.14).

$$Y_i = \delta X_i + P\left(\delta_1 - \delta_0\right)X_i + \sum_{k=1}^{K} \alpha_k P^k + \varepsilon_i \tag{5.14}$$

It is crucial to point out the MTE can only be identified over the support of the propensity score, implying that the greater the variation caused by the relevant instruments between the participants and non-participants in the ROSCAS the larger the range of the support.

The Average Treatment Effect (ATE)[15], Average Treatment on Treated (ATT)[16], and the Average Treatment on Untreated (ATUT)[17] can be obtained by aggregating the MTE over

[15] $ATE = E\left[Y_R - Y_N\right] = E\left[\delta_1(X_i) - \delta_0(X_i)\right]$

[16] $ATT = E\left[Y_R - Y_N \middle| R_i = 1\right] = E\left[\delta_1(X_i) - \delta_0(X_i) \middle| R_i = 1\right] + E\left[\omega_1 - \omega_0 \middle| R_i = 1\right]$

[17] $ATUT = E\left[Y_R - Y_N \middle| R_i = 0\right] = E\left[\delta_1(X_i) - \delta_0(X_i) \middle| R_i = 0\right] + E\left[\omega_1 - \omega_0 \middle| R_i = 0\right]$

the unobserved resistance to participating in ROSCAS (ω_D). The data collection process to run the empirical model follows in the next section.

4.0 Data collection

The data used for this study come from a survey conducted in the three largest cocoa-producing regions in Ghana, between April and July 2018. The regions sampled include the Ashanti, Brong-Ahafo and Western. Currently, the Western region produces more than half of Ghana's cocoa followed by Ashanti region that produces about one-fifth of the cocoa in Ghana.

Using multi-stage sampling procedure, 750 cocoa-producing households were sampled across 24 villages located in 8 districts. To ensure proportionate representation, we sampled four districts from the Western region, and two districts each from Ashanti and Brong-Ahafo. Specifically, Aowin, Sefwi-Akontombra, Sefwi-Juaboso and Bia West were sampled from the Western region. The two sampled districts from the Ashanti region were Ahafo-Ano North and Bosome-Freho districts. Asunafo South and Dormaa East were then sampled from the Brong-Ahafo region.

We conducted a census in the villages to obtain a sampling frame that allowed us to randomly sample our households. Detailed information on farmers' household characteristics, their production activities and all income sources were collected with the aid of computer assisted personal interview (CAPI). In particular, information on all formal and informal groups the household head joined were collected. We also collected the geographical coordinates of the households to derive the rainfall data for 1981 to 2017. From this data, we computed the rainfall anomaly index[18], following the approach by van Rooy (1965). The

[18] Rainfall anomaly index for positive anomalies, $RAI = 3\left[\frac{rain_t - rain_{av}}{rain_{\max 10} - rain_{av}}\right]$ and $RAI = -3\left[\frac{rain_t - rain_{av}}{rain_{\min 10} - rain_{av}}\right]$ for negative rainfall anomalies. Where $rain_t$ is the annual rainfall,

rainfall shock is a normalized deviation from the expected seasonal climatic variable (rainfall) as defined by historical average. We asked a series of questions on shocks households faced to derive a measure of the number of individual-specific shocks experienced (see Table 5.7**A** in the appendix). A group well-trained enumerator conducted the interviews using the local language.

5.0 Results and discussions

This section discusses the results obtained from our analysis. First, we briefly discuss the results obtained from the descriptive analysis. Next, we present and discuss the results from the empirical results. The discussions of empirical results are in three sub-sections: the first sub-section presents and discusses the drivers of selection into ROSCAS. While the second sub-section discusses the heterogeneity in treatment effects on observed characteristics, the third presents and discusses the average and marginal treatment effect estimates on the unobserved characteristics.

5.1 Descriptive results

Table 5.1 presents the variable description and summary statistics of the variables used in our model. Females make up about 25% of our sample, with rest being males, showing proportional representation as shown in the African Development Bank (2015) in the cocoa sector. Nearly half of the sampled farmers can read and write in English. A little over 80 percent reported

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$rain_{av}$ is the average of the annual rainfall, $rain_{\max 10}$ and $rain_{\min 10}$ are respectively average of the ten highest and lowest annual rainfalls.

Table 5. 1: Variable description, summary statistics and mean differences

Variables	Variable description	Full sample	ROSCAS	Non-ROSCAS	Abs. Diff
Panel A: *Outcome variables*					
Fertilizer	Fertilizer expenditure per acre (GHC/acre) (in log)	3.18 (1.72)	3.92 (0.10)	2.85 (0.07)	1.07*** (0.13)
Labor	Expenditure on farm labor per acre (GHC/acre) (in log)	4.26 (1.14)	4.52 (0.07)	4.15 (0.05)	0.37*** (0.09)
Income	Total farm income (GHC) per adult equivalence	7.68 (0.94)	7.86 (0.86)	7.60 (0.97)	0.26*** (0.07)
Panel B					
ROSCAS	1 if a rotating savings and credit associations (ROSCAS) member, 0 otherwise	0.31 (0.46)			
Panel C: *Control variables*					
RainShck	Rainfall shock (measure of covariate risk) in mm	0.83 (1.11)	0.72 (0.07)	0.88 (0.05)	0.16* (0.09)
AvgRain	Average annual rainfall amount (in mm)	1,432.94 (73.46)	1,436.09 (4.66)	1431.49 (74.35)	4.60 (5.78)
IdiosynShck	Idiosyncratic risk (number of shocks households experienced)	0.54 (0.74)	0.64 (0.06)	0.51 (0.03)	0.14** (0.06)
Gender	1 if farmer is female, 0 otherwise	0.25 (0.44)	0.28 (0.03)	0.24 (0.02)	0.03 (0.04)
Age	Age of household head (in years)	52.06 (12.59)	50.99 (0.77)	52.55 (0.57)	1.56 (0.99)
ReadWrite	1 if the farmer can read and write, 0 otherwise	0.47 (0.49)	0.50 (0.03)	0.46 (0.02)	0.04 (0.04)
Married	1 if farmer is married, 0 otherwise	0.81 (0.39)	0.86 (0.02)	0.79 (0.02)	0.07** (0.03)

Indigene	1 if farmer is an indigene, 0 otherwise	0.69 (0.46)	0.74 (0.03)	0.66 (0.02)	0.08** (0.04)
M_Phone	1 if farmer owns a mobile phone, 0 otherwise	0.55 (0.49)	0.53 (0.03)	0.55 (0.02)	0.02 (0.04)
FarmSize	Farm size (in acres)	8.58 (9.22)	8.37 (7.12)	8.68 (10.05)	0.31 (0.73)
Panel D: *Instrumental variables*					
FinConc	Financial concentration, number of formal financial institutions in the district.	4.13 (1.21)	3.78 (0.09)	4.28 (0.04)	0.50*** (0.09)
Distance	Distance from household to district capital (km) 0 otherwise.	8.72 (4.01)	10.90 (0.32)	7.71 (0.14)	3.19*** (0.30)

Notes: This table presents the variable definition, summary statistics and differences in means for participants and non-participants of ROSCAS. For each variable, we present the mean and the standard deviation around the mean for the pooled sample, and then for participants and non-participants in ROSCAS. The differences in means are also presented. Values in brackets are the standard deviations. Exchange rate: 1 US$ = GH₵ 4.73 in August 2018. ***, ** and * respectively denote significance at 1%, 5% and 10% respectively.

being married. Local indigenes make up about 70 percent of our sample. On average, about 4 formal financial institutions[19] operate in each district. The table further reports the mean differences in all variables for participants and non-participants. We find statistically significant differences in the outcome variables between participants and non-participants. For instance, participants in ROSCAS spent about GHC 92 per acre (4.52 in log) on labor compared to about GHC 63 per acre (4.15 in log) by non-participants. Cocoa cultivation is a highly labor-intensive activity, and often family labor has to be complemented with hired labor to carry out timely farm activities. Hence, the ability to hire labor at the appropriate time could significantly influence farmers' output and incomes. The net farm income per adult equivalence[20] is GHC 2,592 (7.86 in log) for participants, and GHC 1,998 (7.6 in log) for non-participants. On average members of ROSCAS invest about GHC 50 (3.92 in log) per acre relative to about GHC 17 (in log 2.85) by non-participants.

Furthermore, ROSCAS members experience on average 0.64 incidence of idiosyncratic risks, which is significantly higher compared to 0.51 experienced by non-participants, implying that participants are more exposed to idiosyncratic risks compared to non-participants. In the contrary, ROSCAS participants are located in villages that experience significantly lower rainfall shocks of 0.72 compared to 0.88 experienced by non-participating farmers. These significant differences in the outcome variables, in particular, do not indicate the impacts of participating in ROSCAS because of potential confoundedness in the participation decisions.

[19] Formal financial institutions include retail and commercial banks, rural banks, savings and loans associations, and credit unions.

[20] Following Regier et al. (2019) we compute the income per adult equivalence using the Deaton and Zaidi (2002) approach $AE_i = \left(A_i + \alpha_i K\right)^{\theta}$ where A_i is the number of adults, K_i is the number of children (below 16 years) $\alpha = 0.33$ and θ=1 or 0.90

5.2 Empirical results

In this sub-section, we present the empirical results from the estimated MTE model. The estimates from the selection equation are first presented and discussed. This is followed by the estimates of the heterogeneity in treatment effects, and finally those of the average returns. In all instances, we present both the results of a parsimonious and the expanded versions of the specifications.

5.2.1 Selection into ROSCAS

Considerable overlap in the characteristics of participants and non-participants in ROSCAS is required for proper identification of the MTE. This is crucial because MTE strongly depends on considerable overlap in characteristics of participants and non-participants, termed, common support to be valid. As seen in figure (1) below, there exist sufficient overlap between participants and non-participants, spanning the desired 0 to 1 probability range.

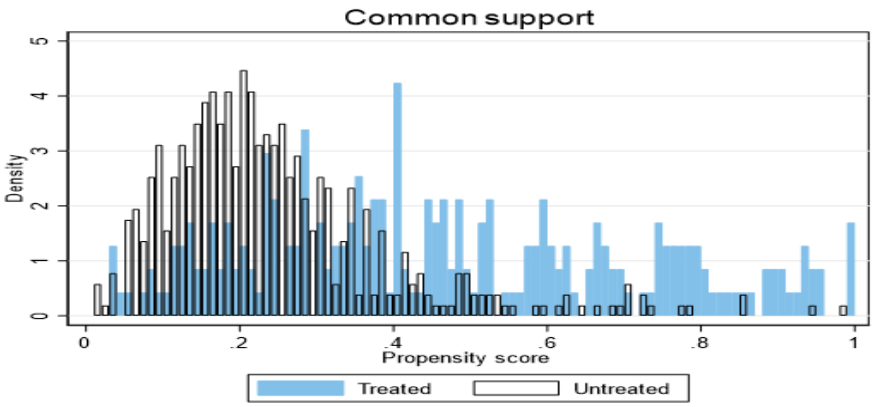

Figure 5. 1: Common support of the propensity scores for participants and non-participants

The first and second columns of Table 5.2 respectively show the coefficients and marginal effects of the parsimonious model. As observed, the instruments used for identifying the model are strong predictors of farmers' participation decision. The estimates show that the variable representing rainfall shock is negative and statistically significant, implying higher rainfall shocks tend to decrease the likelihood of farmers participating in ROSCAS. These findings are

Table 5. 2: Selection equation of the drivers of ROSCAS participation

	Mode1		Model 2	
Variables	Coefficient	Marg. Effects	Coefficient	Marg. Effects
RainSchk	-0.1554***	-0.0538***	-0.1279**	-0.0441**
	(0.0555)	(0.0191)	(0.0582)	(0.0199)
IdiosynShck	0.1374*	0.0475*	0.1499**	0.0517**
	(0.0718)	(0.0249)	(0.0742)	(0.0256)
AvRains			-0.0020**	-0.0007**
			(0.0009)	(0.0003)
Gender			0.0292	0.0101
			(0.1319)	(0.0459)
Age			-0.0088**	-0.0030**
			(0.0044)	(0.0015)
ReadWrite			-0.0249	-0.0086
			(0.1132)	(0.0390)
Married			0.2739*	0.0896**
			(0.1469)	(0.0453)
Indigene			0.2062*	0.0695*
			(0.1246)	(0.0409)
M_Phone			-0.1419	-0.0492
			(0.1116)	(0.0389)
FarmSize			-0.0099	-0.0034
			(0.0068)	(0.0024)
Instrumental variables				
FinConc	-0.3278***	-0.11345***	-0.3839***	-0.1324***
	(0.0487)	(0 .0160)	(0.0574)	(0.0199)
Distance	0.1284***	0.0444***	0.1309***	0.0451***
	(0.0134)	(0.0047)	(0.0137)	(0.0048)
Constant	-0.2457		3.1175**	
	(0.2505)		(1.5104)	
χ^2 test of instruments	142.10***		140.88***	
Pseudo R^2	0.162		0.181	
Observations	750		750	

Notes: This table presents the selection equation of the drivers of ROSCAS participation. ***, ** and * respectively denote significance at 1%, 5% and 10% respectively

quite intuitive given that the rainfall shock, which is covariate in nature, affects the entire village, and therefore reduces the tendency for farmers to participate in these associations. We, however, find positive and statistically significant effect of idiosyncratic risks on participation in ROSCAS. This implies that farmers who face risks specific to them, and independent of the wider village tend to participate in ROSCAS, perhaps due to risk-mitigation role they play (Han et al., 2019; Baland et al., 2021).

The estimates in columns 3 and 4 in Table 5.2 present results after the inclusion of a rich set of control variables. We find similar signs for the variables representing rainfall shocks and idiosyncratic risks in our parsimonious results in the first two columns of this table. The results further reveal that higher average rains decrease the likelihood of participation in ROSCAS. Even though positive, being female tends to have no statistically significant effect on ROSCAS participation. Our findings concur with the findings of Bonan et al., (2019) who found statistically insignificant relationship between gender and participation in ROSCAS in their study in Benin. Our estimates further show negative and statistically significant effect of age on participating in ROSCAS. This suggest that younger farmers tend to participate relative to the elderly. Also, the variable representing married is positive and statistically significant, implying that farmers who are married tend to participate in ROSCAS relative their unmarried counterparts.

As argued by Anderson and Baland (2002), partners in marriages may use ROSCAS as forced-savings mechanisms where there exist significant disparities in the preferences for indivisible goods. Relative to migrants, being an indigene of the local community tends to increase the probability of participating in ROSCAS.

5.2.2 Heterogeneity in treatment effects on observed characteristics

In this section, we present and discuss the estimates of the effects of ROSCAS on investments in fertilizer and labor, as well as farm income. In particular, the estimates show how treatment

Table 5. 3: Heterogeneity in treatment effects in observed characteristics (parsimonious model)

Variables	Fertilizer (1)		Labor (2)		Farm income (3)	
	Outcome(δ_0)	Outcome$(\delta_1-\delta_0)$	Outcome(δ_0)	Outcome$(\delta_1-\delta_0)$	Outcome(δ_0)	Outcome$(\delta_1-\delta_0)$
RainSchk	-0.2273**	1.3819***	-0.1336*	0.5638***	-0.0931*	0.7379***
	(0.1024)	(0.2652)	(0.0687)	(0.1925)	(0.0542)	(0.1719)
IdiosynShck	0.0388	0.1915	-0.0914	0.1126	0.0031	-0.0220
	(0.1854)	(0.3137)	(0.0979)	(0.2095)	(0.0988)	(0.1823)
Constant	2.3367***	-0.4466***	4.1038***	0.1672	6.7507***	0.1641
	(0.2234)	(0.3951)	(0.1675)	(0.3449)	(0.1554)	(0.3047)
p-val obsvd het.	0.000		0.012		0.000	
$rho(\rho)$	-9.1705***		-1.3578		-3.9192***	
	(2.7266)		(1.74)		(1.54)	
Observations	750		750		750	

Notes: Columns 1 and 2 present the estimates of the fertilizer expenditure in the non-participation (δ_0) and participation $(\delta_1-\delta_0)$ respectively. While the 3rd and 4th Colums presents estimates for expenditure on labor, those for farm income are presnted in the 5th and 6th columns. This table also reports the test of observed heterogeneity for participants in ROSCAS. Rho(ρ) provides a test of the presence of selectivity bias. ***, ** and * respectively denote significance at 1%, 5% and 10% .

Table 5. 4: Heterogeneity in treatment effects in observed characteristics (Expanded model)

	Fertilizer (4)		Labor (5)		Farm income (6)	
Variables	Outcome(δ_0)	Outcome$(\delta_1-\delta_0)$	Outcome(δ_0)	Outcome$(\delta_1-\delta_0)$	Outcome(δ_0)	Outcome$(\delta_1-\delta_0)$
RainSchk	-0.28471***	0 .86279**	-0.1454**	0.7039***	-0.0817	0.4802***
	(0.1006)	(0.3514)	(0.0723)	(0.2002)	(0.0600)	(0.2057)
IdiosynShck	0.2368	-0.4573	-0.1182	0.1380	-0.0594	0.0270
	(0.1508)	(0.3286)	(0.1118)	(0.2095)	(0.0935)	(0.1838)
AvRains	0.0032*	0 .0036	0.0019*	-0.0079***	0.0018*	-0.0045
	(0.0017)	(0.0054)	(0.0010)	(0.0026)	(0.0012)	(0.0029)
Gender	0.4409	-1.3280**	0.3773**	0.1308	-0.0082	-0.0278
	(0.2695)	(0.6604)	(0.1625)	(0.3564)	(0.1765)	(0.3809)
Age	0.0042	-0.0309	0.0177***	-0.0188	0.0096	-0.0209
	(0.0107)	(0.0267)	(0.0057)	(0.0133)	(0.0065)	(0.0147)
ReadWrite	0.0015	0.6816	-0.0327	-0.0144	0.2319*	-0.5338
	(0.2366)	(0.6034)	(0.1394)	(0.3163)	(0.1292)	(0.3441)
Married	-0.3784	1.2529	-0.2273	1.1729*	-0.2358	0.2765
	(0.3368)	(1.0424)	(0.2129)	(0.6525)	(0.1567)	(0.5121)
Indigene	0.3071	0.3106	-0.0166	1.0102**	0.1291	0.6325
	(0.2675)	(0.7884)	(0.1926)	(0.4405)	(0.1642)	(0.4835)
M_Phone	0.8353***	-1.7159**	0.3914**	-0.5678	0.4516***	-0.5618
	(0.1109)	(0.6747)	(0.1650)	(0.3831)	(0.1546)	(0.4049)
FarmSize	0.0026	0.0166	0.0025	-0.0265	0.0246**	0.0866**
	(0.0113)	(0.0336)	(0.0060)	(0.0194)	(0.0115)	(0.0379)
Constant	-2.7154	-3.6824	0.1936	11.2146***	3.4119	6.9579*
	(2.4250)	(7.9726)	(1.5646)	(3.8695)	(1.5523)	(4.0479)
p-val obsvd het.	0.010		0.000		0.010	
$rho(\rho)$	-4.6003*		-1.6601		-4.6003*	
	(2.6704)		(1.5028)		(2.6704)	
Observations	750		750		750	

effect varies based on the observed attributes of non-participating (δ_0) and participating $(\delta_1 - \delta_0)$ farmers in ROSCAS.

Tables 5.3 and 5.4 present parsimonious and expanded versions respectively. The estimates in Table 5.3 reveal that in the non-participation stage, all the outcome variables are negative and statistically significant. In particular, for farmers who experienced higher rainfall shocks, while their investment in fertilizer decreased by about 22 percentage points, that for labor decreased by 13 percentage points. It is therefore not surprising that the farm income in the non-participation stage also decreased by about 9 percentage points. However, in the participation stage, investments in fertilizer, and labor increased by 138 and 13 percentage points, respectively. The increased investments in these indivisible inputs could be attributed to the ability for participants to purchase indivisible inputs as pointed out in the literature (Handa and Kirton 1999; Kloner 2003; Sedai et al., 2021). These increased investments led to a 74-percentage points increase in farm incomes in the participation stage. Our findings confer with Czura and Klonner (2018) who argued against the widely held view that non-market financial institutions such as ROSCAS play insignificant roles in coping with covariate risks.

Estimates of the expanded model in Table 5.4 show similar patterns as estimates of the parsimonious model. In terms of the additional covariates, our results reveal that while being an indigene tend to increase investments in labor in the participation stage, its effects in the non-participation, albeit also positive, is statistically insignificant. Recall from the estimates from the selection equation in Table 5.2 shows that on average indigenes tend to be more likely to participate in ROSCAS relative to migrants. These findings suggest that when indigenes form ROSCAS they tend to gain more relative to their migrant counterparts.

Interestingly our estimates also reveal that owning a mobile phone increases investment in farm inputs among the non-participants, while among participants in ROSCAS, owning a

mobile phone decreases investment. These findings are not surprising in that from the results of the selection equation, owning a mobile phone decreases the tendency of farmers to participate in ROSCAS (see results in Table 5.2), because participants are more likely to reside in remote areas where cell phone connections are poor. Hence non-participating farmers who live in areas with better cell phone connections, are able to leverage the financial services provided by mobile telecommunications companies to borrow and invest in farm inputs (Batista and Vicente 2020).

Although the variable representing farm size is positive and statistically significant in both the treated and non-treated states for the farm income outcome, the magnitude is much higher for the participants (8.7 percentage points) compared to non-participants (2.4 percentage points). The findings imply that even though farming on larger farm size increases incomes across board for both participants and non-participants in ROSCAS, the gains in terms of farm incomes is much higher if farmers participate in ROSCAS.

5.3 Treatment effects on the unobserved characteristics

As previously indicated in the empirical specification section of this paper, the MTE identifies the treatment effects evaluated at the means of the observed covariates along the entire distribution of the unobservable characteristics. This helps in gaining insights on whether the gains from participating varies based on the level of resistance to participation.

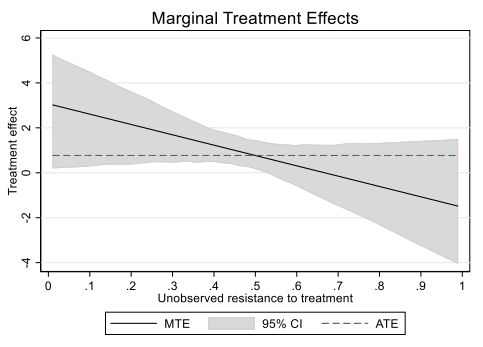

Fig 5.2a: MTE curve for fertilizer

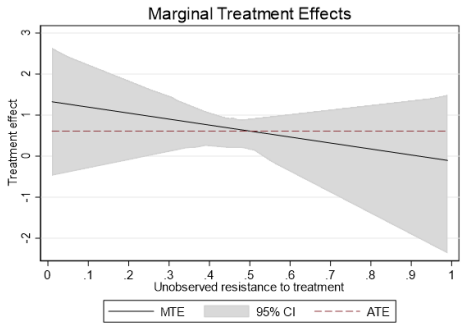

Fig 5.2b: MTE curve for labor

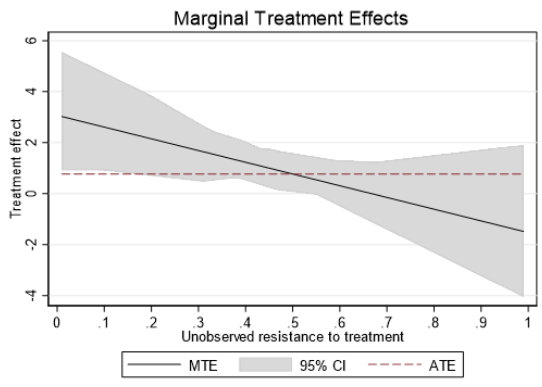

Fig 5.2c: MTE curve for farm income

Figure 5. 2: Marginal treatment effect curves for outcome variables

Figure 5.2 displays the marginal treatment effects curves estimated at the mean values of the covariates. The curves are downward sloping, implying that gains from participation is higher at lower resistance to participation. That is, farmers with lower unobserved resistance to participate in ROSCAS tend to benefit the most from doing so. These findings are indicative of positive selection on gains on unobservable characteristics.

Tables 5.5 and 5.6 present the average gains from participating in ROSCAS for the parsimonious and the expanded models. For all the parameter estimates, the coefficients of the parsimonious are comparatively higher than the expanded model specifications. We, however, would discuss the estimates of the expanded model. The results show that the ATE for investments in fertilizer and labor are 0.77 and 0.59 respectively, implying that a randomly sampled farmer increases investments in fertilizer and labor by about 77 and 59 percentage point respectively from participating in ROSCAS. However, the impact on farmers who participated (ATT) are increased investments in fertilizer and labor by 195 and 108 percentage points respectively. From the farm income outcomes perspective, the results reveal that the ATE and ATT are respectively 62 and 123 percentage points.

Table 5. 5: Average returns to participating in ROSCAS (Parsimonious model)

Parameter	Farm inputs		Income
	Fertilizer	Labor	Farm income
ATE	0.8071***	0.6977***	0.7652***
	(0.2599)	(0.2486)	(0.1680)
ATT	3.1746***	1.0158**	1.7488***
	(0.7312)	(0.4515)	(0.4768)
ATU	-0.2792	0.5518	0.3141
	(0.4685)	(0.3955)	(0.3325)

Notes: This table presents the treatment effect parameters. Estimates of the average treatment effect (ATE), the average treatment effect on the treated (ATT), and average treatment on the untreated (ATUT) are presented. Values in brackets are bootstrapped standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10%

Table 5. 6: Average returns to participating in ROSCAS (Expanded model)

Parameter	Farm inputs		Income
	Fertilizer	Labor	Farm income
ATE	0.7695***	0.5877**	0.6194***
	(0.3650)	(0.2461)	(0.15763)
ATT	1.9472***	1.0822***	1.2381***
	(0.7509)	(0.4957)	(0.4123)
ATU	0.2293	0.3604	0.3356
	(0.5450)	(0.3816)	(0.2976)

Notes: This table presents the treatment effect parameters. Estimates of the average treatment effect (ATE), the average treatment effect on the treated (ATT), and average treatment on the untreated (ATUT) are presented. Values in brackets are bootstrapped standard errors. ***, ** and * respectively denote significance at 1%, 5% and 10%.

On the average treatment on the untreated (ATUT) parameter estimates, our results show statistically insignificant on investments in farm inputs (i.e. fertilizer and labor), and farm incomes, suggesting that participating in ROSCAS would bring little benefits to non-participants. Obviously, these findings appear to show clear evidence of structural hinderances in bringing non-participants to participating in ROSCAS. For example, based on the results of the selection equation we find farmers who do not own mobile phones are more likely to participate, perhaps due to the poor or non-existent mobile phone coverage in their localities. With the increasing financial services offered through mobile network providers, these farmers may be excluded and would have to rely on these informal institutions. We also observe similar patterns in terms of distance from formal financial institutions, with farmers residing far away having higher propensity to participate in ROSCAS compared to those residing closer to these formal institutions. Our results generally reveal positive selection on gains from participating given that for each treatment effect parameters, we find the effect for participants higher than the effect from a randomly selected farmer, and those not participating. (ATT>ATE>ATUT).

6.0 Conclusions and implications

Addressing risk-induced poverty is at the forefront of numerous development policies in many developing countries. Efforts at tackling these challenges through the design and implementation of crop insurance has been met with phenomenal failure among the poor. An often-cited constraint to their update is the lack of understanding. In this study, we examine the risk mitigation role of an informal institution, rotating savings and credit associations (ROSCAS). It is a widely held view that these informal institutions tend to often provide some insurance against idiosyncratic risks to stimulate investments. Regarding whether the insurance from informal institutions is sufficient against aggregate risks remain highly contested. This study employs the marginal treatment effect (MTE) model to estimate both the average

treatment effects of participating in ROSCAS and the distribution of the impacts on unobserved resistance to their participation decisions. Gaining insights on both the observed and unobserved impacts of participation have serious implications for policy purposes.

The empirical results reveal substantial heterogeneity in the impacts of ROSCAS on investment in farm inputs such as fertilizer and labor, and farm incomes. Among the covariates of the selection equation, while we find higher incidence of individual-specific (idiosyncratic) shocks increase participation in ROSCAS, measures of aggregate (covariate) shocks rather decrease participation. These findings are in line with the widely held view that these informal groups appeal to individuals with the objective of addressing idiosyncratic shocks (Udry 1994; Fafchamps and Gubert 2007).

Our findings further reveal that farmers who experience rainfall shocks and do not participate in ROSCAS, decreased investments in fertilizer and labor, that resulted in lower farm incomes. However, among participating farmers, we find significant increases in investments in these inputs even under aggregate shocks such as rainfall shocks. As Czura and Klonner (2018) argue, despite the general doubts concerning the effectiveness of ROSCAS in providing insurance under aggregate shocks, our findings show that indeed ROSCAS.

From a policy perspective, while efforts are made to introduce formal insurance to address significant risks to increase investments among the rural poor, informal financial institutions such as ROSCAS should not be relegated to background. Rather, these informal institutions should be strengthened to step in to play similar roles as the formal insurance, while efforts are made to address the major constraints associated with formal insurance can offer some insurance to spur investment in farm input.

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Appendix:

Table 5. 7A: Individual-specific shocks experienced

Type of shock	***Response*** 1=Yes 0= No
[ ] Experienced bush fires?	
[ ] Experienced disease attack?	
[ ] Encounter loss of land due to tenure issues?	
[ ] Experienced serious health problem that prevented you or other household member from working?	
[ ] Did any of your family members die that you were directly responsible for funerals and other expenses?	
[ ] Other(s)	

Chapter Six

General Conclusions

In the face of worsening climatic and factor market conditions, farmers in sub-Saharan Africa (SSA) are exposed to a barrage of risks and uncertainties in their production activities. In their attempt to mitigate these risks and uncertainties, they often make decisions that are sub-optimal, impeding their efforts of escaping poverty. Researchers and policy makers in response to these concerns, have introduced agricultural insurance to mitigate these risks and uncertainties. Unfortunately, uptake has been disappointingly low. The low agricultural insurance uptake co-existing with evidenced risk aversion among farmers remains a major puzzle till date. Despite the growing evidence, studies on the behavioral factors driving the uptake of agricultural insurance remains scant. Also, there is inadequate studies that review and synthesize the growing body of literature. This study has made four main contributions to deepen our understanding. First, this study has comprehensively reviewed the literature, showcasing the state of the art on agricultural insurance in developing and emerging countries. Second, the study has developed and empirically tested a model to show how risk and ambiguity preferences, and liquidity constraints influence crop insurance uptake. Third, this study has examined the effects and implications of time preferences on the uptake of crop insurance. Finally, this study assessed the impact of rotating savings and credit associations (ROSCAS) on investments in farm inputs and welfare. The detailed summary and key findings are presented in the subsections below:

6.1 Recent Advances in the Analyses of Agricultural Insurance in Developing and Emerging Economies

A comprehensive synthesis of the growing body of the voluminous literature on agricultural insurance programs identified the lack of trust, liquidity constraints, the partial coverage of farmers' risks, and the sheer lack of understanding of the insurance product in developing and

emerging economies. The review also found risks and ambiguity aversion, and time preferences as some of the main behavioral factors driving the low uptake of agricultural insurance in developing countries. Based on these findings, two promising developments that could be leveraged to address most of these constraints include making quality data available, both for the purposes of the design the insurance products, and to improve the understanding of the farmer. The study also recommends that while efforts are underway to develop innovative insurance products for annual crops, attention should also be given to perennial crops because of the less flexibility inherent in production.

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

In this study, we developed a theoretical model to show how risks and ambiguity aversions, as well as liquidity constraints influence farmers' decisions to participate in crop insurance programs. From a series of incentivized field experiments, farmers' risks and ambiguity preferences were measured, and using discrete choice model, the study empirically tested the theoretical model. The results from the empirical analysis revealed that farmers who are risk-averse are more likely to participate in crop insurance compared to risk-loving farmers. In line with the theoretical proposition, the study found ambiguity-averse farmers are less likely to participate in take up crop insurance programs. Farmers who are liquidity-constrained also tend not to participate in the insurance program. Another important finding from the study is the positive and statistically significant effect of literacy on the decisions to participate. These findings imply that efforts should be made to better communicate and explain the workings of crop insurance through trainings and workshops. Relaxing liquidity constraint through, for example, deferred premium payments until harvesting could make it more attractive to increase uptake. Finally, the study recommends governments and other actors to leverage the available

mobile technologies to make yield data easily accessible to farmers to decrease uncertainties on the formation of priors on yields.

6.3 Delayed premium payments improve crop insurance uptake, but at what costs? The role of time preferences

In this study, the role of time preferences on crop insurance uptake is investigated. The widespread liquidity constraints in SSA led to researchers recommending farmers to defer insurance premium payments until harvest to relax the liquidity constraints to improve uptake. However, insurance product does not only transfer incomes among states of nature, but also across time, suggesting that time preferences could play a crucial role. The study employs linear and quantile regression to estimate the drivers of time preferences, and a hybrid model to jointly estimate attributes of the crop insurance products and attribute processing techniques, and other attitudinal variables to avoid potential endogeneity issues. The empirical results reveal that farmers' time preferences are characterized by intrapersonal time inconsistencies, exhibiting impatience in the short-run. The study found literacy level, household income, and subjective assessment of health status as the main drivers of time preferences. Interestingly, the study found farmers residing in communities where artisanal mining takes place to be more impatient compared to their counterparts residing in a non-mining community. Farmers tend to derive positive utilities from higher levels of coverage and insurance product managed by government. However, they derive disutility from insurance managed by licensed buying companies (LBC), and products with higher critical yield levels. From a policy perspective, while efforts are made to relax liquidity constraints through delay in insurance premiums, it is crucial to also institute commitment devices to nudge farmers to honor their promises to repay at harvest periods.

6.4 The impact of informal risk mitigation measures on input use and welfare: Evidence from rotating savings and credit associations (ROSCAS) in Ghana

This last study examined the impact of rotating savings and credit association (ROSCAS) on investments in farm inputs and farm incomes. Given the low uptake of agricultural insurance, recent studies propose a re-consideration of ROSCAS because of their tendency to provide some form of insurance, particularly against idiosyncratic shocks. However, their role under covariate has often been debated in the economic literature. This study applies the marginal treatment effect (MTE) framework that simultaneously accounts for selection bias and heterogeneity across farming households. From the empirical results, the study found farmers with high propensity to participate in ROSCAS invest more in farm inputs and earn significantly higher farm incomes compared to non-participants. Furthermore, the results revealed that farmers who experienced higher covariate risks and participated in ROSCAS tended to mitigate the risks to increase investments in farm inputs. Through the increased investments, ROSCAS participants earned significantly higher farm income compared to non-participants. Based on these findings, the study recommends that while efforts are made to improve the uptake of agricultural insurance, informal institutions such as ROSCAS should be strengthened in the interim to mitigate risks to enhance investments.

Appendices A: Questionnaire

OraI Informed Consent Script

Introduction

This survey aims at gathering data on cocoa farmers' preferences and willingness-to-participate in crop insurance programs in Ghana. The data collected will exclusively be used for academic purposes. Under no circumstance will your private information be passed on to a third party.

Your participation in answering these questions is entirely voluntary. Your answers will be extremely beneficial towards the achieving the aims of this study. We will respect any decision you make about answering our questions. Choosing not to answer these questions or to stop answering them will not have any consequences for you. We would however appreciate if attempt is made to answer all the applicable questions.

It will take about an hour and half (90 minutes) of your time.

Do you wish to participate in this survey? (Enumerator: Mark that verbal consent was given)

[ ] Yes [ ] No

Section A: Basic Identifying Questions

1.1 Region: Ashanti ☐ Western ☐ Brong-Ahafo ☐

1.2 District name: _____

1.3 Community name: _____

1.4 GPS coordinates: N_____:_____:_____

W/E_____:_____:_____

1.5 GPS coordinates of formal financial institutions: : N_____:_____:_____

W/E_____:_____:_____

1.6 Number of formal financial institutions in district: _____

1.7 Community type: [ ] *Mining* [ ] *Non-mining*

1.8 Name of enumerator: _____

1.9 Date of interview: _____/_____/2018

2.0 Name of respondent(s) _____

_____

_____

2.1 Nickname, (if any): _____

2.2 Popular name of HH residence: _____

2.3 Telephone number (s): _____

Section A

A2: Socio-demographics

	Type of household	[ ] Adult female no Adult Male (FNM)
		[ ] Adult Male no Adult Female (MNF)
		[ ] Both Adult Male and Female (MAF)
	Gender of household head	[ ] Male [ ] Female
	What is your age?	_____(years)
	What is your marital status?	[ ] Single (never married) [ ] Cohabitating
		[ ] Married [ ] Divorced
		[ ] Widowed
	Religious affiliation	[ ] Christianity [ ] Islam
		[ ] Traditionalist [ ] None
	What is your ethnicity	[ ] Akan [ ] Northerner
		[ ] Ga Adangbe (Including Ewe) [ ] Non-Ghanaian
	What is your level of formal Education?	[ ] None [ ] Basic [ ] Secondary/vocational/technical
		[ ] Tertiary [ ] Other (Specify)
	Actual number of years of formal education	_____ (years)
	Can you read and write?	[ ] Yes [ ] No
	Which of the following best describes your status.	[ ] Indigene
		[ ] Local migrant
		[ ] Foreign migrant
	For how long have you lived here?	_____ (years)
	Total household size	_____
	No. of Males	
	Males <16 yrs	
	Males btn 16 and 60 yrs	
	Males above 60yrs	
	No. of Females	
	Females <16yrs	
	Females btn 16 and 60 yrs	
	Females above 60 yrs	
	Number of children in school	
	How many of these household members earn income?	
	For how many years have you been farming (personally taking decisions on the farm)	_____ (years)
	Is the household head/any household member engaged in small-scale mining?	[ ] Yes [ ] No

Social Status	
Does the household hold any leadership position in this community?	[ ] Yes [ ] No
If Yes, please indicate arena of leadership	
[ ] Political (e.g. Assembly man, Unit Committee)	
[ ] Traditional (Chief, sub-chief etc.)	
[ ] Religious (Imam, Elder, etc.)	
[ ] FBO/CSO (e.g. Chairperson, Secretary etc.)	
[ ] Others (Specify)	
Distance to tared road? (miles) _____	

Section B1: Exposure to shocks

1.Have you experienced any serious economic shock, such as crop loss over the past 3 years?

[ ] Yes [ ] No

2. If Yes, please complete the table below:

Type of shock	***Response*** 1=Yes 0=No	***Freq.***	***Coping strategy*** *1=Relied on savings 2=Sold livestock 3=Financial support from relatives 4=Financial support from neighbours 5=Others(Specify)*
I. Experienced bush fires?			
ii. Experienced disease attack?			
iii. Encounter loss of land due to tenure issues?			
iv. Experienced serious health problem that prevented your or your household member from working?			
v. Did any of your family members die that you were directly responsible for funerals and other expenses?			
[ ] Other1(Spec)			

3. Have you (or any household member) missed attending to the farming activities continually for three months because of ill-health in the past 12 months? [ ] Yes [ ] No

4. For the first past 12 months, has the household experienced any incidence of theft? [ ] Yes [ ] No

5. Has the household experience any death over the past 12 months that you least expected to happen?
[ ] Yes [ ] no

B2: Social Capital and Social networks

B2i. Social capital

Grp Type	**Specific group**	***Response***	***If Yes, hold leadership position?***
Farmer group	Member of any ***Cocoa certification*** farmers' group (e.g. Fairtrade, Abrabopa etc.)?	[ ] Yes [ ] No	[ ] Yes [ ] No
	Member of any ***other Farmer-based organization***?	[ ] Yes [ ] No	[ ] Yes [ ] No
Credit group	Member of ***Rotating Savings & Credit Association*** (ROSCAs)	[ ] Yes [ ] No	[ ] Yes [ ] No
	Member of ***Village Savings and Loans*** (VSLS) group	[ ] Yes [ ] No	[ ] Yes [ ] No
Religion group	Member of ***Religious group (e.g. Men's Fellowship)*****?**	[ ] Yes [ ] No	[ ] Yes [ ] No
Farmers' Pension scheme	Are you a member of any farmer-based pension scheme (e.g. Cocoa Abrabopa Pension Scheme (CAPS))?	[ ] Yes [ ] No	[ ] Yes [ ] No
Others	Membership of other groups (Community youth groups, Cultural groups etc.)	[ ] Yes [ ] No	[ ] Yes [ ] No

B2ii: Social Networks

Information flow

				Formal Insurance information exchange					
ID	Name	Do you know […]? ***1 = Yes*** ***0 = No*** (Skip to next name)	For how long have you known […]? (in years)	Ever communicated to […] on your health insurance **purchasing *decisions***? ***1=Yes 0=No***	If Yes, how often for the past 12 months?	What information was exchanged on ____ ***1=sources*** ***2=premiums*** ***3=terms and conditions*** ***4=Other***	Ever exchanged info ***Agricultural insurance*** purchasing decisions? ***1=Yes 0=No***	Ever exchanged info ***Life insurance*** purchasing decisions? ***1=Yes 0=No***	Ever exchanged info ***pension insurance*** decisions? ***1=Yes 0=No***
1.									
2.									
3.									
4.									
5									
Link to progressive (successful) farmers									
6	<<<Pre-filled>>>								
7	<<<Pre-filled>>>								

	Agricultural Information exchange						
ID	Ever exchanged Information on ***insecticides for cocoa pdn***? ***1=Yes 0=No***	Ever exchanged Information on ***fertilizer for cocoa pdn***? ***1=Yes 0=No***	Ever exchanged Information on ***weedicides for cocoa pdn***? ***1=Yes 0=No***	Ever exchanged information on ***Other crops?*** ***1=Yes 0=No***	Ever exchanged information on ***Farm animal production?*** ***1=Yes 0=No***	Ever communicated to […] on your short-term **purchasing /*financial decisions***? ***1=Yes 0=No***	Ever communicated to […] on your long-term **purchasing /*financial decisions***? ***1=Yes 0=No***
1.							
2.							
3.							
4.							
5							
6	<<<Pre-filled>>>						
7	<<<Pre-filled>>>						

Financial flow

	Informal insurance						***Savings and Credit membership???***		***Land transaction/Exchange***		
ID	Ever given/received ***financial support? 1=Yes 0=No***	No. of times in the 2016/17 season	Amount given// received	Reason for the receipt/transfer ***1=Family support 2=Agricultural purposes 3=Loan repayment 4=Other(Spec)***	Ever given / received ***food assistance***? ***1=Yes 0=No***	Exchanged other resources in times of disaster (e.g. drought) ***1=Yes 0=No***	Ever being in a ROSCAs with […]? ***1=Yes 0=No***	Ever given ***money*** to [...] to ***guard/keep***? ***1=Yes 0=No***	Ever engaged in land/land related transaction? ***1=Yes 0=No***	Type of transaction ***1=Mortgage 2=Purchased 3=Share tenancy 4=Other(Spec)***	Duration (years)
1.			//								
2.			//								
3.			//								
4.			//								
5			//								
Link to progressive (successful) farmers											
6			//								
7			//								

Social learning

ID	Name	Is […] registered with any insurance provider (e.g. health)? ***1=Yes 0=No***	Which type of insurance product? ***1=Health 2=Pension (e.g. Abrabopa) 3=Life 4=Crop 4=Other(Spec)***	What dominant variety of cocoa does […] cultivate? ***1=Hybrid 2=Amazon 3=Tetteh Quashie (Amelonado)***	How many cocoa farms does […] operate?	Did […] apply fertilizer on his/her farm? ***1=Yes 0=No***	Did […] apply weedicide on his cocoa farm(s)? ***1=Yes 0=No***	Did […] apply organic manure (e.g. poultry manure) on his/her farm? ***1=Yes 0=No***	Is […] a subscriber to any ***mobile-phone based extension*** services? ***1=Yes 0=No***	How many bags of cocoa did [..] obtain last year? (64 kg bags)
1.										
2.										
3.										
4.										
5										
6	<<<Pre-filled>>>									
7	<<<Pre-filled>>>									

Characterizing the network

ID	Name	How are you related to […]? ***1=Nuclear family*** ***2=Extended family*** ***3=Same ethnic grp*** ***4=Neighbour*** ***5=Same religion*** ***6=All migrants*** ***7=Same Association*** ***8=Other(Spec)***	Do you use the same footpath to the farm as this person? ***1=Yes*** ***0=No***	Ever visited […] farm? ***1=Yes*** ***0=No***	Is your farm adjacent to […]? ***1=Yes*** ***0=No***	What is the distance between your farm and that of […]? (miles)	Ever visited […] house? ***1=Yes*** ***0=No***	Walking time from your house to […]? (minutes)	
1.									
2.									
3.									
4.									
5									
6.	<<<Pre-filled>>>								
7.	<<<Pre-filled>>>								

SECTION C: Preferences for Crop Insurance

C1: Awareness on crop insurance

1.0 Have you ever purchased/taken part in ***any*** insurance program (including health)?

[ ] Yes [ ] No

2.0 Are you aware of any agricultural insurance policy that you could purchase to protect any crop or livestock against losses?

[ ] Yes [ ] No

2.1 If Yes, please can you name them:

_____

_____

3.0 Do you know of any agricultural insurance program specifically meant for cocoa farmers?

[ ] Yes [ ] No,

3.1 If Yes, please list them

_____

_____

Section C2: Contingent valuation and Choice Experiment on Crop Insurance

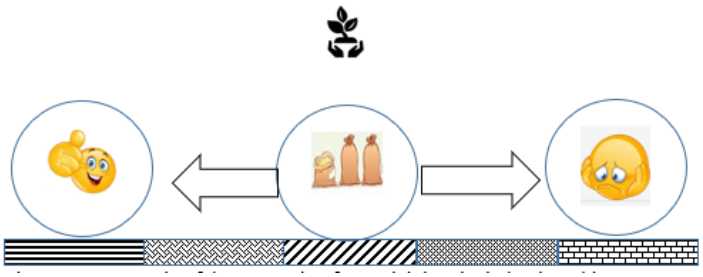
Cheap Talk Script

Before we commence, I would like to talk about a challenge that has been identified in previous studies of similar nature. Most people act differently in situations where they have to really pay for a good or service than in situations where they do not make payments. That is, they say something but do something differently. For example, some people state high prices which under normal real-world situation they will not buy an item at that price.

Among others, the reason accounting for this is that in real situations people take into account their household budget. It could also possibly be that people are unable to clearly picture what product they are being offered for them to make the decisions. Please, do you understand what I am talking about?

Now, we want you to behave in the same way that you would really do in making such decisions and paying to participate in the program, taking cognizance of what you really want and the alternatives presented. It is also important to take into account other constraints that I have not highlighted in this situation. Please, try to put yourself in a realistic situation and act as you would in a real-world situation.

C2.1.1 Contingent valuation for Area yield insurance (Take-it-or-leave it (TIOLI)



Note to Enumerator: Please explain clearly to the respondent what area-yield entails with the aid of the diagram above.

Are you willing to participate in an area yield insurance program that costs [randomly select: GHC 100, GHC 120 or GHC 140] per acre of your cocoa farm?

[ ] Yes [ ] No

C2.2: Choice experiment on Ideal Area Yield Insurance Program

Block 1

C2_1

Product characteristics	***Insurance X***	***Insurance Y***	
Critical yield level	388kg per hectare	194kg per hectare	
Coverage	25%	75%	
Management	Government	Private Insurance Agents	***No Buy***
Payment period	Planting	Harvesting	
Premium	GHC 120	GHC 120	
I will choose …	☐	☐	☐

C2_2

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	388kg per hectare	
Coverage	75%	25%	
Management	Government	Private Insurance Agents	*No Buy*
Payment period	Harvesting	Planting	
Premium	GHC 150	GHC 120	
I will choose …	☐	☐	☐

C2_3

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	194kg per hectare	
Coverage	25%	75%	
Management	Private Insurance Agents	LBCs	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 100	GHC120	
I will choose …	☐	☐	☐

C2_4

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	291kg per hectare	
Coverage	50%	25%	
Management	Government	Private Insurance Agents	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 120	GHC 100	
I will choose …	☐	☐	☐

C2_5

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	75%	25%	
Management	LBCs	Private Insurance Agents	*No Buy*
Payment period	Harvesting	Planting	
Premium	GHC 100	GHC 150	
I will choose …	☐	☐	☐
I will choose …			

C2_6

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	291kg per hectare	291kg per hectare	
Coverage	25%	50%	
Management	Government	LBCs	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 120	GHC 100	
I will choose …	☐	☐	☐

C2_7

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	25%	50%	
Management	Government	LBCs	*No Buy*
Payment period	Harvesting	Planting	
Premium	GHC 100	GHC 120	
I will choose …	☐	☐	☐

\C2_8

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	50%	25%	
Management	LBCs	Government	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 150	GHC 120	
I will choose …	☐	☐	☐

C2_9

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	291kg per hectare	
Coverage	75%	50%	
Management	Government	Private Insurance Agents	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 150	GHC 100	
I will choose …	☐	☐	☐

C2_10

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	291kg per hectare	
Coverage	50%	75%	
Management	Government	LBCs	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 150	GHC 120	
I will choose …	☐	☐	☐

C2_11

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	25%	50%	
Management	LBCs	Government	*No Buy*
Payment period	Harvesting	Planting	
Premium	GHC 150	GHC 100	
I will choose …	☐	☐	☐

----------***Block 2***----------

C3_1

Product characteristics	Insurance X	Insurance Y	
Critical yield level	194kg per hectare	388kg per hectare	
Coverage	75%	25%	
Management	Private Insurance Agents	Private Insurance Agents	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 120	GHC 150	
I will choose …	☐	☐	☐

C3_2

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	291kg per hectare	
Coverage	75%	50%	
Management	Government	Private Insurance Agents	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 150	GHC 100	
I will choose …	☐	☐	☐

C3_3

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	291kg per hectare	388kg per hectare	
Coverage	75%	50%	
Management	Private Insurance Agents	LBCs	
Payment period	Planting	Harvesting	*No Buy*
Premium	GHC 100	GHC 120	
I will choose …			

C3_4

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	25%	75%	
Management	Government	LBCs	
Payment period	Harvesting	Planting	*No Buy*
Premium	GHC 100	GHC 150	
I will choose …			

C3_5

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	388kg per hectare	
Coverage	50%	75%	
Management	Private Insurance Agents	Government	
Payment	Planting	Planting	*No Buy*
Premium	GHC 150	GHC 120	
I will choose …			

C3_6

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	50%	25%	
Management	Private Insurance Agents	LBCs	*No Buy*
Payment period	Planting	Planting	
Premium	GHC 100	GHC 150	
I will choose …	☐	☐	☐

C3_7

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	291kg per hectare	
Coverage	25%	75%	
Management	LBCs	Government	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 150	GHC 100	
I will choose…	☐	☐	☐

C3_8

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	194kg per hectare	
Coverage	75%	50%	
Management	Private insurance	Government	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 120	GHC 100	
I will choose …	☐	☐	☐

C3_9

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	291kg per hectare	
Coverage	25%	50%	
Management	Private insurance	Government	*No Buy*
Payment period	Harvesting	Planting	
Premium	GHC 120	GHC 100	
I will choose …	☐	☐	☐

C3_10

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	194kg per hectare	291kg per hectare	
Coverage	75%	25%	
Management	Private insurance	LBCs	*No Buy*
Payment period	Planting	Harvesting	
Premium	GHC 100	GHC 120	
I will choose …	☐	☐	☐

C3_11

Product characteristics	*Insurance X*	*Insurance Y*	
Critical yield level	388kg per hectare	194kg per hectare	
Coverage	50%	25%	
Management	LBCs	Government	*No Buy*
Payment period	Harvesting	Harvesting	
Premium	GHC 100	GHC 150	
I will choose …	☐	☐	☐

CIII: Attribute processing statements

How much do you feel that you considered (attended to) the following attributes in your final choice of the insurance products presented?

CIII1: Attributes	***Never***	***Rarely***	***Sometimes***	***Often***	***Always***
Critical yield level	[ ]	[ ]	[ ]	[ ]	[ ]
Coverage	[ ]	[ ]	[ ]	[ ]	[ ]
Management	[ ]	[ ]	[ ]	[ ]	[ ]
Payment period	[ ]	[ ]	[ ]	[ ]	[ ]
Premium (price for insurance)	[ ]	[ ]	[ ]	[ ]	[ ]

Please rank the level of importance of the following in making your choice of insurance product

1 = First (most) important, 2= Second (most) important, 3= Third (most) important, 4=Forth (most) important, and 5= Fifth (Least) important

CIII3: Attributes	***Relative importance***
Critical yield level	[ ]
Coverage	[ ]
Management	[ ]
Payment period	[ ]
Premium (price for insurance)	[ ]

Section D: Self-reported risk and trust

1. On a scale of -2 to +2, how would you generally describe yourself in taking or avoiding decisions whose outcomes are not certainly known? ***Please note that 0 refers to neither want to take or avoid decisions with uncertain outcomes), -2 means don't want to take chances at all, -1 means somehow tries to avoid risks. On the other end, 1 refers to somehow take decisions with uncertain outcomes and +2 refers to love to take decisions whose outcomes are not known with certainty.***

-2	**-1**	**0**	**1**	**2**
[ ]	[ ]	[ ]	[ ]	[ ]

2. Generally speaking, most people can be trusted or that you cannot be too careful in dealing with people. Please indicate your level of (dis)agreement with this statement

[ ] Strongly disagree [ ] Disagree [ ] Neutral [ ] Agree [ ] Strongly disagree

3. What is your thought on how people will react when they have the chance to take advantage of you? [ ] Take advantage [ ] Be fair

Please indicate your level of (dis)agreement with the following statements, where **-2** refers to ***strongly disagree***, ***-1 disagree***, ***0 neutral*** (indifferent), ***1 agree*** and ***2, strongly agree***.

D4	**Perceptions on some measures of trust**	***-2***	***-1***	***0***	***1***	***2***
i.	If you misplace your money, it is likely to be returned	[ ]	[ ]	[ ]	[ ]	[ ]
ii.	I can trust people in this community with a loan	[ ]	[ ]	[ ]	[ ]	[ ]
iii.	I can trust that when my livestock strays to someone's house, the fellow will inform me to come for the livestock	[ ]	[ ]	[ ]	[ ]	[ ]
iv.	There is relatively high incidence of theft in cocoa growing communities than in other crop growing communities	[ ]	[ ]	[ ]	[ ]	[ ]

D5		***1 = Trust 0=Neutral - 1=Don't trust***
	How would you rate the level of trust you have in the following:	
i.	Household members	
ii.	Extended family members	
iii.	Neighbours	
iv.	Strangers in this community	
v.	Traditional authorities	
vi.	Government institutions	

Section EI: Cocoa production data for 2016/2017 Production season

1. In total, how much land does this household own? _____ (acres)
2. Out of the total land owned, how many acres are under cultivation? _____ (acres)
3. The next section asks questions on all cocoa plots you operated/managed in the 2016/2017 growing season
4. Total number of cocoa plots _____

DII: Plot No.	Plot name (Location: e.g. ***Birim Agya***)	Plot size (acres)	Distance to home (mile)	Years of current cocoa cultivated (years)	Dominant cocoa variety cultivated ***1= Hybrid*** ***2=Amazon*** ***2=Tetteh Quashie (Amelonado)***	Did you do lining and pegging when planting? ***1=Yes*** ***0=No***	Fruit bearing status: ***1=All bearing*** ***2=Partially bearing*** ***3=Not bearing***	If partially bearing, please indicate the approximate percentage ***1=25%*** ***2=50%*** ***3=75%***
1.								
2.								
3.								
4.								
5.								

5. Land Tenure arrangements on cocoa plots

Plot #	**Tenure Type** *1=Owned (purchased)* *2=Owned (Inherited)* *3=Allocated from extended family member* *4= Share tenancy arrangements (**Land owner also bears part of input costs**)* *5=Share tenancy (**Landowner DOES NOT bear the cost of any inputs**)* *6= Fixed rent**(Mortgage)*** *7=Provided in exchange for Planting trees (Taungya)* *8=Caretaker ("Nhw3so")* *9=Other(Spec)*	**Tenure Duration** For tenure 3, 4, 5, … Please indicate the duration of the tenancy contract **(in years)**	**Tenure security** Have you registered this plot of land, and possess a land title? ***1=Yes 2=No***	**Slope** Generally, how will you describe the level of slope on this plot? ***1= Very Steep*** ***2= Slightly Steep*** ***3= Flat***	**Plot quality** In your view, how would you describe the quality of the soil on this plot? ***1 = Good*** ***2 = Average*** ***3 = Poor***
Plot 1					
Plot 2					
Plot 3					
Plot 4					
Plot 5					

6. Cocoa Agroforestry

Plot #	**Apart from cocoa, are there other trees on this plot?** ***1= Yes*** ***0=No***	**How many trees are on this plot?**	**Did you plant these trees yourself?** ***1=Yes*** ***0= No***	**Do you intend to plant more trees on this plot?** ***1=Yes*** ***0=No***	**Perception of trees on cocoa** **1=Decreases yield** **2=Increases yield** **3=No effect**
Plot 1					
Plot 2					
Plot 3					
Plot 4					
Plot 5					

EII: Input Application

Labour

	Labour input	No. of times	Plot 1			Plot 2			Plot 3			Plot 4			Plot 5		
			Fmy	*Hired*		*Fmy*	*Hired*		*Fmy*	*Hired*		*Fmy*	*Hired*		*Fmy*	*Hired*	
			MD[21]	*MD*	*TC*[22]	*MD*	*MD*	*TC*	*MD*	*MD*	*TC*	*MD*	*MD*	*TC*	*MD*	*MD*	*TC*
	A) Pre-harvest labour inputs																
	Manual weed control																
	Pruning																
	Weedicide application																
	Pesticide application																
	Foliar (liquid) fertilizer application																
	Granular fertilizer application																
	B) Harvesting and post-harvest																
	Main Crop season																
	Harvesting																
	Gathering (under trees)																
	Transportation to pod breaking point																
	Pod breaking																
	Fermentation and turning																
	Transportation to point of drying																
	Drying																
	Transportation to Purchasing Clerks (PCs																
	Others(Spec)_____																
	Light Crop Season																
	Harvesting																
	Gathering (under trees)																
	Transportation to pod breaking point																
	Pod breaking																
	Fermentation and turning																
	Transportation to point of drying																
	Drying																
	Transportation to Purchasing Clerks (PCs																

Note: For activities that involve the use of machines/equipment, please 1, as the number for man-days and record the total expenditure in the appropriate column

[21] Man-days (MD) = number of people * number of days this activity was carried out

[22] TC refers to the total cost incurred. Largely applicable to hired labour (including costs on feeding of labour exchange groups (nnoboa))

Other Costs

1.0 Did you purchase drying mat (***Apa/Aserende***) during the 2016/2017 cropping season?
[ ] Yes [ ] No

1.1 If yes, number purchased_____ Cost per unit _____

1.2 Typically how many years are you able to use this drying mat? _____ Years

2.0 Did you rent motorized sprayer for 2016/2017 cropping season? [ ] Yes [ ] No

If Yes, total cost for renting_____ (GHC)

EIII: Cocoa Extension Services

Personal contacts

1. Did cocoa extension agent contact you in the 2016/2017 production season? [ ] Yes [ ] No
   1.1 If yes, how many times were you contacted? _____
2. Did you personally pay a visit to the cocoa extension office for technical advice? [ ] Yes [ ] No
   2.1 If yes, how many times did this happen last year? _____
3. Have you ever attended farmer field/ demonstration farms before? [ ] Yes [ ] No
   3.1 Did you take part in farmer field school/ field demonstration during 2016/2017 season?
[ ] Yes [ ] No

Digital extension systems

4. Are you subscriber to any mobile phone-based cocoa extension services? [ ] Yes [ ] No
   4.1 If yes which type(s)? [ ] Cocolink [ ] Farmerline [ ] Vodafone Farmers Club
   [ ] Others (Spec)
5. Did you receive agricultural information through your mobile phone? [ ] Yes [ ] No
6. Have you ever taken part in a community video extension delivery before? [ ] Yes [ ] No
   6.1 Did you take part in any video extension in the 2016/2017 production season? [ ] Yes [ ] No

EIII: Non-labour inputs

Note to enumerator: For this section, please probe to find the number of times farmers apply these inputs, sum them and enter in appropriate columns

	Non-labour Inputs	No. of times	Plot 1			Plot 2			Plot 3			Plot 4			Plot 5		
			Qty	*UC*	*TC*	*Qty*	*UC*	*TC*	*Qty*	*UC*	*TC*	*Qty*	*UC*	*TC*	*Qty*	*UC*	*TC*
	A)Fertilizer																
	A1. Mineral fertilizer (Granular) (50kg)																
	Asaasewura																
	Cocofeed																
	Ammonia																
	Other (Specify)_____																
	A2. Liquid fertilizer (litres)																
	Super gro																
	Sidalco																
	Lithovit																
	Cocoset																
	Other(Spec)_____																
	A3. Organic manure (e.g. poultry manure)																
	B)Insecticides																
	Akatemaster																
	Confidor																
	Actara																
	Other1 (Specify)_____																
	Other2 (Specify)_____																
	C) Fungicides (1kg)																
	Ridomil																
	Nordox																
	Champion																
	Funguran																
	Kocide																
	Other 1(Spec)_____																
	Other2 (Spec)_____																
	D) Weedicides (litres)																
	Roundup																
	Glyphosate																
	Other(Spec)																

F: Output obtained (2016/2017) cropping season

Refer to respondent's output records (Passbook), if available. If not, please rely on farmer's recall.

Output of cocoa obtained (kg)	***Rounds***	***P1***	***P2***	***P3***	***P4***	***P5***
Main crop season	Round 1					
	Round 2					
	Round 3					
	Round 4					
	Round 5					
Light crop season						
	Round 1					
	Round 2					
	Round 3					
	Round 4					
	Round 5					
Total Output						

Section G: Income, Savings and Credit (liquidity constraint)

G1: Income and Income sources for the 2016/2017 cropping season

	Income source	Obtained income from this source? ***1=yes 0=No***	Income obtained GHC
1	Cocoa		
2	Other tree crops (oil palm, para rubber etc.)		
3	Food crop sales		
4	Livestock sales		
5	Mining		
6	Other non-farm work		
7	Remittance (both within and outside Ghana, including mobile money receipts)		
8	Pension		
7	Other1 (Spec) _____		
10	Other2 (Spec) _____		
11	Other3 (spec) _____		

G2: Savings

Did you save part of the income your household earns 2016/2017 production year?

[ ] Yes [ ] No

If Yes, indicate the means of savings

[ ] Susu (Regular informal savings) [ ] Digital savings (mobile money) [ ] Bank [ ] ROSCAs [ ] Village Savings and Loans Societies [ ] Other (Spec)

How much did you save during the 2016/2017 cropping season? GHC_____

G3: Credit (liquidity) constraint

Did you undertake all relevant cultural practices on appropriate times?	If No, what caused the delay in undertaking the task(s) at the required time?	If liquidity constraint, did you apply/request for credit (from any source)?	If Yes, how much did you apply for?	How much did you obtain?
[ ] Yes [ ] No	[ ] Liquidity constraint [ ] Non-liquidity constraint reasons	[ ] Yes [ ] No	GHC----------	GHC----------

Section H: Risk, Ambiguity, and Time preferences

H1: Risk preferences

H1_1: **Game 1**: Which of the two options do you prefer? Please tick **A** or **B**

	Option A	Option B
Probability	**100%**	**50%** chance of either receiving or Not
Amount	**GH¢ 20**	**GH¢ 40**
I will choose…	☐	☐

Game 2: Which of the two options do you prefer? Please tick **A** or **C**

	Option A	Option B
Probability	**100%**	**50%** chance of either receiving or Not
Amount	**GH¢ 20**	**GH¢ 24**
I will choose…	☐	☐

Game 3: Which of the two options do you prefer? Please tick **A** or **D**

	Option A	Option B
Probability	**100%**	**50%** chance of either receiving or Not
Amount	**GH¢ 20**	**GH¢ 56**
I will choose…	☐	☐

H2: Loss aversion

Now let us assume that there is a change in scenario. Instead of you only receiving (winning) money in the previous experiment, it involves a loss or payment. In each scenario, you are expected to make a choice between the two options presented

F3_1	Option A		Choice		Option B	
			A	B		
1	***Gain*** GHC 20	***Lose*** GHC 9	○	○	***Gain*** GHC 50	***Lose*** GHC 43
2	***Gain*** GHC15	***Lose*** GHC 9	○	○	***Gain*** GHC 50	***Lose*** GHC 43
3	***Gain*** GHC 9	***Lose*** GHC 9	○	○	***Gain*** GHC 50	***Lose*** GHC 43
4	***Gain*** GHC 5	***Lose*** GHC 10	○	○	***Gain*** GHC 50	***Lose*** GHC 43
5	***Gain*** GHC 5	***Lose*** GHC 10	○	○	***Gain*** GHC 50	***Lose*** GHC 43
6	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
7	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
8	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
9	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43
10	***Gain*** GHC 5	***Lose*** GHC 12	○	○	***Gain*** GHC 50	***Lose*** GHC 43

H3: Ambiguity preferences

There is a game where you are going to play, by drawing a ball out of a box without looking. If the ball you choose is the right colour, then it is assumed you win GHC 20. You will decide which of the two boxes to draw the ball from.

I) Game 1:

Box A: In box A, there are ten (10) RED balls and zero (0) BLUE balls. To win, you must pick a RED ball.
Box B: In box B, there are 10 balls-some are RED and some are BLUE. You decide what colour ball wins. You must then pick this colour ball to win.

Which of the two boxes would you prefer to draw the ball? [ ] Box A [ ] Box B

II) Game 2:

Box A: In box A, there are 8 RED balls and 2 BLUE balls. To win, you must pick a RED ball.
Box B: In box B, there are 10 balls-some are RED and some are BLUE. You decide what colour ball wins. You must then pick this colour ball to win.

Which of the two boxes would you prefer to draw the ball? [ ] Box A [ ] Box B

III) Game 3:

Box A: In box A, this time, there are 5 RED balls and 5 BLUE balls. To win, you must pick a RED ball.

Box B: In box B, there are 10 balls-some are RED and some are BLUE. You decide what colour ball wins. You must then pick this colour ball to win.

Which of the two boxes would you prefer to draw the ball? [ ] Box A [ ] Box B

IV) Game 4:

Box A: In box A, this time, there are 3 RED balls and 7 BLUE balls. To win, you must pick a RED ball.
Box B: In box B, there are 10 balls-some are RED and some are BLUE. You decide what colour ball wins. You must then pick this colour ball to win.

Which of the two boxes would you prefer to draw the ball? [ ] Box A [ ] Box B

V) Game 5:

Box A: In box A, this time, there is One (1) RED Ball and Nine (9) BLUE Balls
Box B: There are 10 Balls, some are RED and some are BLUE. Here too, the choice of Only RED Ball Wins.
Which of the two boxes would you prefer to draw the ball? [ ] Box A [ ] Box B

VI) Game 6:

Box A: In box A, this time, there is zero (0) RED Ball and Nine (10) BLUE Balls

Box B: There are 10 Balls, some are RED and some are BLUE. Here too, the choice of Only RED Ball Wins.

Which of the two boxes would you prefer to draw the ball? [ ] Box A [ ] Box B

H4: Time preference (Money-Earlier or Later (MEL)

Please make your choice on the following two scenarios. Imagine you are presented with an immediate amount of GHC 100 and some amount ***one year*** later, which would you prefer?

F3_1	**Option A**	**Choice** A	B	**Option B**
1	Receive GHC 100 **today**	○	○	Forego, GHC 75 **one year** from now
2	Receive GHC 100 **today**	○	○	Forego, GHC 110 **one year** from now
3	Receive GHC 100 **today**	○	○	Forego, GHC 120 **one year** from now
4	Receive GHC 100 **today**	○	○	Forego, GHC 130 **one year** from now
5	Receive GHC 100 **today**	○	○	Forego, GHC 140 **one year** from now
6	Receive GHC 100 **today**	○	○	Forego, GHC 150 **one year** from now
7	Receive GHC 100 **today**	○	○	Forego, GHC 160 **one year** from now
8	Receive GHC 100 **today**	○	○	Forego, GHC 170 **one year** from now
9	Receive GHC 100 **today**	○	○	Forego, GHC 180 **one year** from now
10	Receive GHC 100 **today**	○	○	Forego, GHC 200 **one year** from now

How much does the prize have to be for you to wait for the ***1 year*** to receive it? _____GHC

H4_2: Decision in 5 years vs 6 years

Please make your choice on the following two scenarios. Imagine you are presented with an amount of GHC 100 in ***five years*** and ***Six years*** later, which would you prefer?

F3_4	**Option A**	**Choice** A	B	**Option B**
1	Receive GHC 100 **five years**	○	○	Forego, GHC 105 **six years** from now
2	Receive GHC 100 **five years**	○	○	Forego, GHC 110 **six years** from now
3	Receive GHC 100 **five years**	○	○	Forego, GHC 115 **six years** from now
4	Receive GHC 100 **five years**	○	○	Forego, GHC 120 **six years** from now
5	Receive GHC 100 **five years**	○	○	Forego, GHC 125 **six years** from now
6	Receive GHC 100 **five years**	○	○	Forego, GHC 130 **six years** from now
7	Receive GHC 100 **five years**	○	○	Forego, GHC 135 **six years** from now
8	Receive GHC 100 **five years**	○	○	Forego, GHC 140 **six years** from now
9	Receive GHC 100 **five years**	○	○	Forego, GHC 145 **six years** from now
10	Receive GHC 100 **five years**	○	○	Forego, GHC 150 **six years** from now

How much does the prize have to be for you to wait for the ***5 years*** to receive it? _____GHC

H4_5 Consideration of future consequences (CFC) scale

Please indicate your level of (dis)agreement with the following sets of statements

Note: ***1***= *Strongly disagree* ***2***= *Disagree* ***3***=*Neutral/indifferent* *4=Agree* *5=Strongly Agree*

	Consideration of future consequences (CFC)	1	2	3	4	5
1.	I think about things in the future and I try to influence these in everyday life.	[ ]	[ ]	[ ]	[ ]	[ ]
2.	I often deal with things that will have consequences in several years.	[ ]	[ ]	[ ]	[ ]	[ ]
3.	I am only concerned about the present, assuming it will turn out all right in the future.	[ ]	[ ]	[ ]	[ ]	[ ]
4.	I only think about the immediate consequences of my actions (several days/weeks).	[ ]	[ ]	[ ]	[ ]	[ ]
5.	Whether something is convenient determines my decisions to large extent.	[ ]	[ ]	[ ]	[ ]	[ ]
6.	I am prepared to sacrifice my current well-being in order to achieve objectives in the future.	[ ]	[ ]	[ ]	[ ]	[ ]
7.	I think that it important to take warnings about negative future results of my actions seriously, even if these results will materialize in the distant future.	[ ]	[ ]	[ ]	[ ]	[ ]
8.	I believe it is more important to deal with matters that will have major consequences In the future, than to deal with matters with immediate but minor consequences.	[ ]	[ ]	[ ]	[ ]	[ ]
9.	I generally ignore warnings about future issues, because I assume that these problems will be solved by then	[ ]	[ ]	[ ]	[ ]	[ ]
10.	I believe that there is no need to make sacrifices now for future issues, because these could be solved later.	[ ]	[ ]	[ ]	[ ]	[ ]
11.	I only respond to urgent problems, supposing that I can deal with future problems when they emerge.	[ ]	[ ]	[ ]	[ ]	[ ]

H5: Trust games (protocol)

Instruction

In this section, you will be confronted with a decision that involves money. The amount of money you earn will depend on choices you and another participant in this research will make. It may also happen that you may earn nothing. The other participant is also a household head in this village. That person is in our survey. You will not know who the other participant is, and the person will also not know who you are. Your choice and the outcomes will be strictly confidential. Please do not talk to anyone during the experiment.

You will be given two envelops, one with (…) and an empty one. You are expected to take this money and put it into the empty envelop to be sent to another person.

Please record the following

Sender	**GHC**
Code on the envelop (please record this but don't ask respondent)	
How much did you find in the envelop?	
How much did you keep for yourself?	
How much did you send?	

Receiver	**GHC**
Code on the envelop (please record this but don't ask respondent)	
How much did you find in the envelop?	
How much did you keep for yourself?	
How much did you return?	

Section J:

J1: Yield risk and Crop insurance perception

Note: ***1****=Strongly Agree* ***2****= Agree* ***3****=Neutral/indifferent* *4=Disagree* *5=Strongly disagree*

A	**Yield risk perception**	1	2	3	4	5
1.	I obtain on the average ***lower*** yield (Bags/acre) compared to other	[ ]	[ ]	[ ]	[ ]	[ ]
	Farmers in this community.					
2.	I obtain on the average the ***same yield*** compared to other farmers	[ ]	[ ]	[ ]	[ ]	[ ]
	in this community.					
2.	Over the past five years, I have observed significant variation.	[ ]	[ ]	[ ]	[ ]	[ ]
	in the yield obtained compared to others in this community.					
3.	I expect my yield to significantly decrease in the near future.	[ ]	[ ]	[ ]	[ ]	[ ]
B	**Crop insurance perception**					
4.	Crop insurance is NOT relevant for me because of my small	[ ]	[ ]	[ ]	[ ]	[ ]
	Cocoa farm.					
5.	Crop insurance will be important in the future (e.g. 10 years) and	[ ]	[ ]	[ ]	[ ]	[ ]
	Not now.					
6.	There is no need for crop insurance because government will	[ ]	[ ]	[ ]	[ ]	[ ]
	come to our aid should disaster strike.					

J2: On a scale of 1 to 5, what do you think is the likelihood that you will obtain cocoa yield of 3.0 Bags per acre next year?

1=Very unlikely 2=Unlikely 3=Possible 4=Likely 5=Very likely

1	**2**	**3**	**4**	**5**
[ ]	[ ]	[ ]	[ ]	[ ]

Section L: Household Wealth and health information

1.0 Livestock Ownership	Response	Number Owned	***Current*** Unit price GHC	***Current*** Total Value
1.1 Cattle	[ ] Yes [ ] No			
1.2 Goat	[ ] Yes [ ] No			
1.3 Sheep	[ ] Yes [ ] No			
1.4 Pig	[ ] Yes [ ] No			
1.5 Chicken	[ ] Yes [ ] No			
1.6 Duck	[ ] Yes [ ] No			
1.7 Turkey	[ ] Yes [ ] No			
1.8 Guinea fowl	[ ] Yes [ ] No			
1.9 Other (Specify)_____	[ ] Yes [ ] No			
2.0 Household wealth				
2.1 Car	[ ] Yes [ ] No			
2.2 Motorcycle	[ ] Yes [ ] No			
2.3 Bicycle	[ ] Yes [ ] No			
2.4 TV	[ ] Yes [ ] No			
2.5 Decoder (e.g. Multi TV, Strong etc.)	[ ] Yes [ ] No			
2.6 Radio	[ ] Yes [ ] No			
2.6 Mobile Phone(s)	[ ] Yes [ ] No			
2.7 Other1(Spec)	[ ] Yes [ ] No			
3.0 Farm tools				
3.1 Hoe	[ ] Yes [ ] No			
3.2 Cutlass	[ ] Yes [ ] No			
3.3 Go-to-hell (Sickle for harvesting cocoa)	[ ] Yes [ ] No			
3.4 **Motorized sprayer**	[ ] Yes [ ] No			
3.5 Knapsack Sprayer	[ ] Yes [ ] No			
3.6 Spade/Shovel	[ ] Yes [ ] No			
3.7 Wheel barrow	[ ] Yes [ ] No			
3.8 Other (Spec)	[ ] Yes [ ] No			
			Current value (GHC)	
Do you own a house?	[ ] Yes [ ] No			
Own building plot(s)?	[ ] Yes [ ] No			
Own ceremonial clothes (e.g. Kente, wax prints)	[ ] Yes [ ] No			
Own jewelries?	[ ] Yes [ ] No			

Section M: Brief health Information

1. Are you a registered member of the national health insurance? [ ] Yes [ ] No
2. What is the status of your health insurance? [ ] Active [ ] Expired
3. Do you consume alcohol? [ ] Yes [ ] No
4. How will you describe your alcohol consumption? [ ] Occasional [ ] Light drinker [ ] Heavy drinker
5. What is the source of water for the drinking? [ ] Mechanized borehole [ ] Borehole (not mechanized) [ ] Well [ ] Stream/River/Pond/Lake [ ] Other (specify) _____

Appendix B: Curriculum vitae

Williams Ali
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24116 Kiel, Schleswig-Holstein
Mobile: +49 152 1073 0135
Email: wilalii@hotmail.com

Personal information

Place of birth: Kumasi, Ghana
Nationality: Ghanaian

Qualifications

Date	Qualification	Institution
Nov. 2022	PhD Agricultural Economics DISSERTATION: Essays on formal and informal risk management: Behavioral insights on Cocoa farmers in Ghana	University of Kiel, Germany
Nov. 2015	MPhil. Agricultural Economics	Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
Jun. 2009	BSc. Agriculture (Agric. Economics Option)	Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Other

Dec. 2020	Data, Economics and Development Policy (DEDP), MITx MicroMaster	Massachusetts Institute of Technology (MIT)

Research interests

Primary Fields: Behavioral Development Economics & Risk assessment and management

Secondary Fields: Experimental economics and Quasi-experimental impact assessment

Work Experience

Year	Role	Assignment
2017 - now	Research Assistant	Carry out academic tasks assigned by the Chair of the Institute of Food Economics and Consumption Studies, University of Kiel
2016	Consultant	USAID/METSS & WFP Joint Case Study on the Economic Benefits and Sustainability of Maize Smallholder Farmers in Northern Ghana
2016	Supervisor and Data Management Expert	Overseas Development Institute's (ODI) Food Security Impacts of Industrial Crop Expansion in sub-Sahara Africa (FICESSA)
2016	Supervisor	USDA's Ghana Poultry Project (GPP) Baseline Study- Value Chain Analysis in poultry sector

2016	Supervisor	West African Agricultural Productivity Programs' (WAAP) Evaluation of the Impact Mining on Root and Tuber Productivity
2016	Supervisor	Randomized Controlled Trial on Ghana Nutritional Improvement Project by UTokyo and JICA
2015	Data Management Expert	French Development Agency's (AfD) Assessment of the Impact of Rubber Cultivation on Food Security and Income
2015/2013 2012	Field Team Member	Baseline, Midline and Endline Data collection (Using Computer Assisted Personal Interview, CAPI) on World Food Program's Purchase for Progress Program (P4P)
2014/2013	Technician	Integrated Seed Sector Development (ISSD) Ghana's Scoping Study (BMGF Sponsored)
2013	Supervisor	Endline Evaluation of the Impact of ICT on Productivity of Cocoa (World Cocoa Foundation (WCF) funded)

Teaching experience

SoSe-2022	Teaching Assistant	Modeling Consumer Behavior (Graduate level Course, University of Kiel, Germany)
WiSe-2022 -2021	Teaching Assistant	Econometric Methods in Agriculture and Food Economics (Graduate level course, University of Kiel, Germany)
2013/2014	Demonstrator/Graduate Assistant	Research Assistance and organization of tutorial Class for Undergraduates (at the Department of Agricultural Economics, Agribusiness and Extension), KNUST-Ghana
2010	Research/Teaching Assistant	Research Assistance and organizing tutorial Class for Undergraduates (at the Department of Agricultural Economics, Agribusiness and Extension), KNUST-Ghana

Publications

2021

Risk, Ambiguity and willingness to participate in crop insurance programs: Evidence from a field experiment (with Awudu Abdulai, Renan Goetz and Victor Owusu) published in *Australian Journal of Agricultural Economics.*

https://doi.org/10.1111/1467-8489.12434

Preferences for crop insurance attributes among cocoa farmers in Ghana (with Victor Owusu and Awudu Abdulai) published in *Journal of Agribusiness in Developing and Emerging Economies*

https://doi.org/10.1108/JADEE-03-2021-0068

2020

Recent Advances in the analyses of demand for agricultural insurance in developing and emerging countries (with Awudu Abdulai and Ashok K. Mishra) published in *Annual Review of Resource Economics.*

https://doi.org/10.1146/annurev-resource-110119-025306

Refereeing Activities

Agricultural Economics,

Theory and Decision,

International Journal of Disaster Risk Science

Competencies

Computer:

Competent at programming questionnaires in CAPI using **ODK**, **Kobocollect** & **SurveyCTO**

Advance user of **STATA,** Intermediate in **R,** and basic **in Python programming**

Language: English (Official); Deutsch (Niveau B1); French (Basic)

Referees

Prof. Dr. Awudu Abdulai
(Chair)
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