RISK, PREFERENCES AND ADAPTATION STRATEGIES OF FARMERS IN GHANA

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FOREWORD

Economic preferences of individuals play a significant role in almost every important economic decision. For instance, whenever costs and benefits for an individual or household are uncertain, it is essential to calculate the present value certainty equivalents in order to undertake meaningful comparisons. The extent to which people are willing to take risk constitutes their risk and time preferences. In effect, assessing and measuring the economic preferences of individuals is critical for economic analysis and policy prescriptions (Charness et al., 2013). For example, risk preference is identified as one of the main drivers of farm management and land use decisions (Chavas et al., 2010; Jianjun *et al.*, 2015). Also, the risk preference of farmers is identified as a major player in agricultural production decision (Feder, 1980; Just and Zilberman, 1983; Adger et al., 2009). In addition to risk preferences, socio-cognitive processes of decision makers are also suggested to be important for motivating adaptation decision (Jordan and McDaniels, 2013; Jianjun et al., 2015).

Agriculture, which plays a major role in the livelihoods of households in the sub-Saharan Africa and serves as a stimulus for economic growth, providing food security and assisting in poverty reduction, is identified to be susceptible to risks and uncertainty (Cervantes-Godoy et al., 2013; Ellis, 2017). These risks and uncertainty may come from a wide range of factors including vagaries of weather, the unpredictable nature of biophysical processes, the pronounced seasonality of production and market cycles, the geographical separation of production and end uses, and the unique and uncertain political economy of food and agriculture sectors, both domestic and international (Jaffee et al., 2010). These shocks are mainly faced by rural households and these increase their vulnerability to both transient and chronic poverty.

Climate shock is ranked among the most pervasive stresses that face rural households (Ziervogel and Calder, 2003) especially in developing countries where rural livelihoods are inextricably linked to the natural environment[1] (Mensah and Adu, 2015). In addition, Barrett et al. (2007) argues that, weather risks and climate shocks are critically important constraints to wealth accumulation, particularly for those in rural areas who are either engaged in agricultural activities or have their livelihoods tied to the well-being of the farming sector. This is because, when climate shocks strike, its immediate impacts among other things are

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destruction of crops, damage to property, loss of savings and assets and threats to health and nutrition. These short-term costs of climate shocks according to the United Nations Development Programme (2008), can have devastating and highly visible consequences for human development.

Adaptation and mitigation are considered the most important policy options in reducing the impact of climate shock (IPCC, 2014). However, because of the frustration over the lack of process and effectiveness of policy to reduce greenhouse gas emissions, a surge in interest in impact oriented action is discernible since the beginning of the century, in contrast to efforts centred on prevention (Burton et al, 2002). Thus, there has been a shift from mitigation towards adaptation over the years. In effect, adapting to climate change has consequently emerged as a solution to address the impacts of climate shocks and these are already evident in some regions.

Adaptation seeks to lower the risks posed by the consequences of climate shocks and it involves changes in agricultural management practices in response to changes in climate conditions. It often involves a combination of various individual responses at the farm-level and assumes that farmers have access to alternative practices and technologies available in the region. However, most adaptation strategies are characterised by risk and uncertainty. Thus, the issue of better characterizing risk and time preferences may be particularly important as adaptation programs are meant to introduce new products to farmers. However, before institute policies are instituted to reduce the impact of climate shocks on income from production and how effectiveness these strategies will be, it is important to first estimate the impact of climate shocks on income from crop production in Ghana. This is what I did in the first paper of this thesis.

An econometric model to estimate a stochastic production function that quantifies the effects of climate variables (average temperature and precipitation) and other inputs (area cultivated, trend and agricultural labour force) on the mean, variance and skewness of real per capita income from crops was adopted. One major finding was the effect of precipitation and variation in precipitation on real per capita income from crops. The results show that, even though, both variables do not have significant effect on per capita income from crop production, they both contribute to increasing downside risk exposure. In other words, annual precipitation and variation in precipitation increases the probability of crop failure, thereby, reducing per capita income from crop production.

After confirming the fact that precipitation and variation in precipitation significantly increases the probability of crop failure, I focussed on investigating how different degree of exposure to flood, which is caused by variability in precipitation, impact on the behavioural traits of farmers and their decision-making process in adopting adaptation strategies, which is considered as one of the most important policy options in reducing the impact of climate shocks (IPCC, 2014). In particular, I exploit a natural experiment implied by different degree of exposure to risk in terms of flood and the effects these risks have on the behavioural traits of farmers, and their willingness to adopt adaptation strategies.

Contrary to standard economic hypothesis that individuals' preferences are fixed, the results show that preferences are not stable, with exposure to risks making people more risk averse, impatient and more cooperative. The results also show that exposure to different degree of risk has a significant effect on adaptation strategies, but the main channel through which it impacts respondents' adaptation decisions is through risk aversion. In particular, being exposed to high degree of risk makes respondents less likely to access credit to invest in their farms, more willing to pay higher agricultural insurance premium and more willing to contribute higher amount for the construction of drainage systems to reduce the impact of flood on their farms and households. In effect, by reducing the exposure to risk, policy makers can obtain less risk averse households and thereby making it easier to implement adaptation strategies.

Estimating the Risk Involved in Food Crop Production in Ghana

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Abstract

Risk and uncertainty are ubiquitous and varied within the agricultural sector coming from a wide range of factors including vagaries of weather, the unpredictable nature of biophysical processes, market cycles and enabling environment. This study was used to investigate how weather risk and climate shocks and other agricultural inputs impact real per capita income from food crop production in Ghana. An econometric model to estimate a stochastic production function that quantifies the effects of these variables on the mean, variance and skewness of real per capita income was adopted. The results show that average temperature has a significant concave relationship on real per capita income, indicating that rising average temperature increases real per capita income but the increase in real per capita income diminishes as average temperature increases above a maximum 27.78°C. Precipitation on the other hand does not have any significant effect on real per capita income on the average. It was, however, found to have a risk decreasing effect on the variability in real per capita income but increases the probability of crop failure resulting in low real per capita income. It was also revealed that, whereas variability in average temperature was found to reduce the probability of crop failure, variability in annual total precipitation was found to increase the probability of crop failure and thus reduces real per capita income. Future research will focus on how different degree of exposure to the risk flood impact on the behavioral traits of farmers and their decision-making process in adopting adaptation strategies.

1. Introduction

Risk and uncertainty are ubiquitous and varied within the agricultural sector in both developed and developing countries, and even though the sources and consequences may differ between countries they are generally experienced by most farmers in most countries. These risks and uncertainty may come from a wide range of factors including vagaries of weather, the unpredictable nature of biophysical processes, the pronounced seasonality of production and market cycles, the geographical separation of production and end uses, and the unique and uncertain political economy of food and agriculture sectors, both domestic and international (Jaffee et al., 2010).

Agriculture plays a dominant role in the livelihoods of households in the sub-Saharan Africa, serving as a stimulus for economic growth, providing food security and assisting in poverty reduction. However, poverty and food insecurity are critical issues for most countries in sub-Saharan Africa with one of the major cause of these problems attributed to agriculture's susceptibility to production, price and policy risks which impact farmers' income and welfare (Cervantes-Godoy et al., 2013; Ellis, 2017). Even though there has been a decline in agricultural sector's performance and its contribution to most socioeconomic indicators, the sector still plays a central role in the Ghanaian economy. For instance, the sector still absorbs the highest proportion of the Ghanaian total employed population, with about 36% of the labour force employed in agricultural sector. It is worth noting that about 84% of the agricultural labour force are in the rural areas (GSS, 2016).

Crop production in Ghana is risky as it is mainly rain-fed and prone to a number of shocks including: climatic shocks, pest and diseases, bushfires and price shocks (Choudhary et al., 2015). These types of shocks affect different types of crops and can result in the reduction of the national value of production. For instance, the national maize yield has decreased by an average of 2.5% every year for the past half-decade (MOFA, 2016). Production risk, which include weather risks and climate shocks, bushfires and pest and diseases, is ranked among the most pervasive stresses that face farmers (Choudhary et al., 2015) especially in developing countries where rural livelihoods are inextricably linked to the natural environment[2] (Mensah and Adu, 2015).

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According to Rosenzweig and Binswanger (1993), while several factors contribute to household income variability, rainfall variability is likely to influence welfare the most, particularly because it is spatially covariant. Barrett et al. (2007) also argues that, weather risks and climate shocks are critically important constraints to wealth accumulation, particularly for those in rural areas who are either engaged in agricultural activities or have their livelihoods tied to the well-being of the farming sector. This is because, when climate shocks strike, its immediate impacts among other things are destruction of crops, damage to property, loss of savings and assets and threats to health and nutrition. These short-term costs of climate shocks according to the United Nations Development Programme (2008), can have devastating and highly visible consequences for human development.

In effect, before we institute policies to whether adapt or mitigate the effects of climate shocks on income from crop production and the effectiveness of policies to reduce these impacts, it is important to first estimate the impact of climate shocks on income from crop production in Ghana. Even though in the long run the extent to which the degree of sensitivity of crop production depends on technological change, crop climate adaptation (adoption of high yielding varieties, improved planting and management practices, the use of fertilizer and pesticides etc.) and CO2 fertilization, examining historical data and relating production variability to climate can identify how agricultural productivity is sensitive to climate change. This paper will thus examine and understand how weather risk and climate shocks impact real per capita income from agriculture in the country.

2. Literature Review

Since the late 1970's, the literature addressing climate change impacts has made conscious effort to shift from literature based on "expert opinion" surveys on the impacts of climate change on agriculture to dynamic multi-region, multi-sector economic models. Among the first efforts to assess the agricultural impacts of climate change was undertaken by National Defense University (NDU) in 1978 (Darwin et al., 1995). The study assembled an international group of climate experts and elicited their opinions concerning the probabilities of various climate change events and the resulting impacts on agriculture. The notable finding of the study was experts disagreeing on most matters related to climate change (Darwin et al., 1995). Many efforts have since then been made to measure the economic impact of climate change on agriculture, initially focusing mainly on the United States and other developed countries (Adams, 1989; Mendelsohn et al., 1994; Bruce et al., 1996; Reilly et al., 1999). However, little research was focused specifically on the developing countries even though some experts (Fankhauser, 1995; Pearce et al., 1996) have extrapolated their results of findings worldwide. In recent times, while some studies have been conducted to assess the impact of climate change on agriculture in developing countries (Dinar et al., 2008; Kumar and Parikh, 1998; Mendelson et al, 2000; Deressa et al., 2005; Kurukulasuriya, 2006; Seo and Mendelsohn, 2006; Maddison et al., 2007; Molua and Lambi, 2007; Seo and Mendelsohn, 2008a, Seo et al., 2009; Deressa and Hassan, 2009), very little research has been carried in Ghana to study climate change impacts on agriculture.

Various models have been used to assess the impact of climate change on agriculture. Each of these models has various advantages and disadvantages and they also present different levels of complexity and completeness in relation to the specific aspects that are considered in their analysis. The two main methods that have been used include: the structural modelling method which, relies on empirical or experimental production functions to predict environmental change (Mendelsohn et al., 1994) and the spatial analogue models, which uses econometric approaches and economic data on the value of land to analyse the impact of climate on agriculture across different climate zones. Other impact assessment methods that have been used are the integrated impact assessment method and the agro-ecological zone (AEZ) method (Mendelsohn, 2000).

Three major components under the structural modelling method include: Physiological studies, crop simulation models, and economic models. Physiological research addresses how changes in weather (e.g. temperature and precipitation) and other factors affect crops. Crop modeling studies, on the other hand, simulates how yields change under different conditions, whether using historical data or future projections and economic studies examine how yields change when market interactions are considered and how this affects prices, production, consumption, and trade. Each component of the research is influenced by other factors such as climate stress (precipitation, temperature, availability of water, among others) based on General Circulation Model (GCM) results and may include information on specific technologies, such as drought and heat tolerance (Islam et al., 2016).

Crop simulation models can be divided into two types, which rely on a large set of projected climate change effects from various GCMs that take into account temperature, precipitation, water stresses, and other variables, include: crop simulation models that are process-based and statistical models that are reduced form. Process-based models specify agents and their behaviour in dynamic systems to estimate the effects of counterfactual changes (Islam et al., 2016; Chetty, 2009; Sims, 1986). The reduced form models, on the other hand, describe relationships among selected variables while holding others constant and estimate statistical relationships. In addition, the reduced form statistical analyses use historical and field trial data to estimate relationships between yield and climate variables which are then used to project yields into the future under various GCMs (Islam et al., 2016). The production function approach, which is based on experimental or empirical analysis of the relationships between yield and environmental factors (Chang, 2002), is an example of the reduced form model.

In all, the basic idea of these approaches is that agricultural production growth depends on soil-related climatic variables and socio-economic variables that are implemented as explanatory variables in the model for estimating the production function (Chang, 1977; Randall, 2001; Fleischer et al., 2008). Therefore, under these approaches, yield sensitivity to climate change is estimated by assessing the empirical production function that links water, soil, climate and economic input to yields for specific crops. This is because climate variables play an important role in determining crop yields or production since climatic factors are related to important stages in plant phenology. For example, precipitation with germination and flowering; and temperature with development and maturation of the fruit. Plant development also depends on their exposure to moisture and temperature during their growing stage.

The spatial analogue approach, which uses cross-sectional evidence to undertake statistical (econometric) estimations of how changes in climate would affect agricultural production across different climatic zones, include: The Future Agricultural Resources Model (FARM) by Darwin et al. (1994, 1995); and the Ricardian approach by Mendelsohn et al. (1994). The basic underlying assumption for these models is that similar climates mean similar production practices. This assumption allows the models to implicitly capture changes in production inputs, crop or livestock outputs or management practices that farmers are likely to adopt in response to changing climatic and other conditions (Darwin, 1999).

Early research on the impact of a changing climate focused mainly on the different effects of climate change on crop production using crop simulation models. In one of the earliest studies, Newman (1980) under this model concluded that the United States Corn Belt would shift northeast for every 1˚C rise in temperature. Another crop simulation study by Blasing and Solomon (1984) concluded that the United States Corn Belt would contract particularly in its southwest region, under warmer and drier growing seasons. In a similar analysis, a study by Rosenzweig (1985) revealed that climate change would increase winter wheat production in Canada, while the major effect in the United States would be regional shifts in the use of wheat cultivars. A series of case studies by Parry *et al.* (1988) also concluded by not taking into account CO2 effects or adaptation that warmer temperature in high-latitude countries will by the lengthening of the growing season increase crop production. However, the study revealed that higher evapotranspiration will lead to adverse effects on crop yields.

Warrick (1984) also used a regression to simulate temperature increases similar to those that occurred in the 1930's in the United States and found that crop production decreased. Another study by Terjung *et al.* (1984), who employed the production function approach to estimate the impact of climate change and deduced that the amounts of water for irrigation would have to be greater when faced with rising temperatures if no technological changes were made. In a study by Easterling *et al.*, (1993) in the United States using the production function approach, it was revealed that in the absence of technological changes or increases in CO2, climate change would bring about reductions in production resulting in economic losses.

Early studies on the impact of climate change on agriculture from developing countries also predominantly relied on structural modeling approaches with limited adaptation. For example, Seshu and Cady (1984) estimated a decrease in rice yield in India at the rate of 0.71 tonnes per hectare given an increase in minimum temperature from 18˚C to 19˚C. The study also shows that an increase in minimum temperature from 22˚C to 23˚C will result in a decrease in rice yield in India at a rate of 0.41 tonnes per hectare. In a similar analysis, Sinha and Swaminathan (1991) found that an increase in mean air temperature by 2˚C could reduce rice by about 0.75 tonnes per hectare in the high-yield areas and by 0.06 tonnes per hectare in the low-yield coastal areas. The study also revealed that a 0.5˚C increase in winter temperature would reduce wheat crop duration by seven days and decrease yield by 0.45 tonnes per hectare. In addition, the increase in winter temperature is estimated to account for a 10 percent reduction in wheat production in high-yield areas. In another crop simulation study, Aggarawal and Sinha (1993) show that a 1˚C rise in mean temperature in North India would have no significant effects on wheat yields. They, however, concluded that a 2˚C increase in mean temperature would reduce yields in most places.

The main weakness of the structural modeling approach was that it endorses the so-called "dumb-farmer" hypothesis, which excludes from it analysis farmer's behaviour and farmer's management practices, which includes the plausible adoption by farmers of strategies for coping with the effects of climate change. In other to overcome this limitation, Mendelsohn *et al.* (1994) proposed the Ricardian model which estimates the relationship between the outcomes of farms and climate normal using and including, among regressors, the appropriate control variables (De Salvo *et al.*, 2013). In effect, it considers farmer's management strategies implicitly without the need to implement such strategies as explanatory variables (Mendelsohn and Dinar, 2009).

In view of this critique about excluding from it analysis farmer's behaviour and farmer's management practices, some structural modeling approaches in the literature successfully introduced adaptation into crop simulation models (Jin et al., 1994; El-Shaer et al., 1997; Kapetanaki and Rosenzweig, 1997; Iglesias and Minguez, 1997). These farm level studies begin with agronomic models but then examine efficient responses by farmers to climate change using an economic model of the farm. In other words, adaptation is addressed by simulating changes in the growth parameters of various crops according to the latest scientific advances. However, these models fail to account for economic considerations and limitations in human capital and other resources that affect actual farm-level decisions (Mendelsohn, 2000) which makes it difficult to interpret the adaptation scenarios frequently explored. This is because farmers are likely to respond to changing climate and other environmental factors by varying, among other things, the crop mix, planting and harvesting dates, irrigation scheduling and application of fertilizers and pesticides to mitigate the potential harmful effects of climate change.

The production function approach, which is the model used in this study, generally link the outputs of crops or livestock as functions of inputs to the production process, such as land, labour, capital and entrepreneurial skill. These inputs can be incorporated individually, or as an index, such as the Laspeyres Quantity Index, which can combine any physical inputs together. The basic idea of this approach is that agricultural production growth depends on soil-related and climatic variables that are implemented as explanatory variables in the model for estimating the production function (Chang, 1977; Randall, 2000). Therefore, under this approach, yield sensitivity to climate change is estimated by assessing the empirical production function that links water, soil, climate and economic input to yields for specific crops. The effect of climate change is assessed by considering the yield variations comparing two alternative scenarios using general circulation model (De Salvio et al., 2013).

While the production function approach is the least common approach used to model the impacts of climate change on agricultural outputs to date, it is empirically sound. One advantage of this approach is that it provides estimates for climate change effect on crop yields that do not include bias due to agricultural output factors such as soil quality that are beyond the control of the farmer (Deschenes and Greenstone, 2007). A further advantage of the production function approach is that it takes into consideration historical farm level and aggregated data and thus able to account for farmer's historical reactions to changes in climatic and economic conditions.

It has also been adopted to account for the impact of climate change on the agricultural sector in developed countries (Warrick, 1984; Terjung *et al.*, 1984; Easterling *et al.*, 1993; Deschenes and Greenstone, 2007) and developing countries (Turpie et al., 2002; Isik and Devadoss, 2006; Poudel and Kotani, 2013). Even though several studies have used the production function approach and the stochastic production function approach to measure the impact of climate change on agriculture and the risk of the changing climate on crop yield (Chang, 2002; Schlenker *et al.*, 2006; Isak and Devadoss, 2006; Deschênes and Greenstone, 2007), higher moments of the stochastic production function has not been considered explicitly. We, therefore, argue that the higher moments of the stochastic production function should be exploited to estimate the risk of the changing climate on crop yield. The Just and Pope stochastic production function will thus be adopted to measure the impact of climate change on mean crop productivity and higher order variations of crop yield (Antle, 1983) in Ghana.

3. Data

3.1 Agriculture in Ghana

Ghana lies within latitude 4˚44'N and 11˚11'N and 3˚11'W and 1˚11'E longitude covering approximately 238,500 km^2. It is located on the south coast of West Africa and bordered in the west by Cote d'Ivoire, to the east by Togo, to the north by Burkina Faso and to the south by the Gulf of Guinea. Administratively, the country is divided into 10 regions and 170 districts. The overall topography is low and gently undulating with most slopes of less than 5 percent and many not exceeding 1 percent. Despite the gentle slopes, approximately 70% of the land is susceptible to significant erosion (MOFA, 2013). The country is composed of six agro-ecological zones, which are distinguished by natural vegetation and influenced by climate and soil characteristics (see Figure 1).

Fig. 1: Map of Ghana showing agro-ecological zones.
Source: Kemausuor *et al.* (2013).

Variation in precipitation and temperature are controlled by the movement and interaction of continental and maritime winds. The evergreen rain forest, deciduous rain forest, transition and coastal savannah zones make up the southern half of the country. These agro-ecological zones have a bimodal equatorial rainfall pattern, allowing for two growing seasons (major and minor growing seasons) (see Table 1). The greater part of the three northern regions is covered by the Guinea savannah, but part of the Upper East region is covered by the Sudan savannah. These agro-ecological zones (Sudan and Guinea Savannah) benefit from a single tropical monsoon, allowing for only one major growing season (see Table1) (Hielm and Dasori, 2012). This single growing season is bound by the harmattan period, which begins in December and ends in March.

Table 1: Precipitation and growing seasons in Ghana by agro-ecological zone

Agroecological Zone	Area (km^2)	Mean Annual Prec.	Annual Prec. Range	Major Rainy Season	Minor Rainy Season	Growing Period (days)	
						Major Season	Minor Season
Rain Forest	9500	2200	800-2800	Mar-July	Sept-Nov	150-160	100
Deciduous Forest	66000	1500	1200-1600	Mar-July	Sept-Nov	150-160	90
Transition Zone	8400	1300	1100-1400	Mar-July	Sept-Nov	200-220	60
Coastal Savannah	4500	800	600-1200	Mar-July	Sept-Nov	110-110	60
Guinea Savannah	147900	1000	800-1200	May-Sept		180-200	
Sudan Savannah	2200	1000	800-1000	May-Sept		150-160	

Source: FAO, 2005 and MOFA, 2013.

A total of 136,000 km^2 representing approximately 56.9 percent of Ghana's total land area is classified as agricultural land (MOFA, 2016). Of the total agricultural land, approximately 47.2 percent is under cultivation, and only about 3.4 percent of the cultivated area is irrigated. The major crops cultivated in Ghana include numerous cereals, root and tuber, fruit, legumes, vegetable and industrial crops (FAO, 2005). The staple crops include cereals (maize and rice), roots and tubers (yam and cassava) and legumes (groundnuts and cowpea). Vegetables (tomatoes and pepper) and fruits (orange, avocado and mango) provide essential micronutrients. In 2015, the total land area used to cultivate annual crops, which include cereals, tubers, legumes and vegetables was approximately 12000km^2 (MOFA, 2016). The industrial crops, which are cash crops for export revenue, include cocoa and oil palm. Smallholder rain-fed farming using rudimentary technologies dominates the agricultural sector accounting for 80% of total agricultural production and approximately 90% of smallholder farms are less than two hectares in size, and produce a diversity of crops. Larger farms and plantations primarily cultivate cocoa, oil-palm, rubber and coconut, and to a lesser extent, cereals and pineapples (MOFA, 2013).

Table 2: Principal crops grown in agro-ecological zones

Agroecological Zone	Cereals	Starchy crops	Legumes	Vegetables	Tree crops
High Rain Forest	Maize, rice	Cassava, cocoyam, plantain		Pepper, okra, eggplant	Citrus, coconut, oil palm, rubber
Deciduous Rain Forest	Maize, rice	Cassava, cocoyam, plantain	Cowpea	Pepper, okra, eggplant, tomato	Citrus, coconut, coffee, cocoa
Transition Zone	Maize, rice, sorghum	Cassava, cocoyam, plantain, yam	Cowpea, groundnut	Pepper, okra, eggplant	Citurs, coffee, cashew
Coastal Savannah	Maize, rice	Cassava	Cowpea	Tomato, shallot	Coconut, pineapple,
Guinea Savannah	Maize, rice, sorghum, millet	Cassava, yam	Cowpea, groundnut, soybean, bambara	Tomato, pepper	Sheanuts, cashew
Sudan Savannah	Maize, rice, sorghum, millet	Sweet potato	Cowpea, groundnut, soybean, bambara	Tomato, onion	

Source: FAO, 2005 and MOFA, 2013.

According to Food and Agricultural Organisation (2005) the physical and biological characteristics of the agro-ecosystem, as well as socioeconomic factors, dictate what crops and farming systems will produce the greatest benefits or lowest risk to the farmer and household. The major crops grown in the six agro-ecological zones are presented in Table 2. Maize and rice are grown in all regions, while sorghum and millet are grown primarily in the transition and northern savannah zones. Starchy crops and vegetables are grown in all regions. Legumes production occurs in all regions except for the high rainforest, and tree crop production is common in all regions except for the Sudan Savannah. Tropical tree crops are also generally restricted to the southern agro-ecological zones, with the exception of sheanut and cashew, which occur in the northern savannah.

3.2 Source and Data Description

This study seeks to examine the impact of climate related variables (precipitation and temperature) and other crop production inputs on mean per capita income from crop production and the variability in per capita income. Therefore, secondary data on food crop production and climate variables were obtained from some major research institutions in Ghana. Annual food crop production and the total cropped area for nine major crops (maize, rice, cassava, yam, cocoyam, plantain, millet, sorghum and groundnut) were obtained for all districts in Ghana from the Statistical, Research and Information Directorate (SRID) department of the Ministry of Food and Agriculture (MOFA) from 1990 to 2015. Data on the average annual price of these crop was also obtained from the website of Food and Agriculture Organization (FAO) and the Ghana Statistical Service (GSS). I also collected data on the total regional population and the number of people engaged in agriculture from the Ghana Statistical Service (GSS) from 1990 to 2015. Monthly data on climate variables (precipitation and temperature) were also obtained for all the 10 regions in Ghana from the Ghana Meteorological Agency (GMA) from 1990 to 2015.

The analysis of crop production shows that the production of crops is very concentrated in some regions. The results show that, while rice is grown in all ten regions of Ghana, the top three regions (Northern, Upper East and Volta) accounted for nearly 74 percent of total national output. It can be observed that most of the crops produced in the country are concentrated in three regions (Brong Ahafo, Eastern and Ashanti) out of the ten regions. These three regions together produced over half of most of the food crops produced in the country. In particular, the Ashanti region, Brong Ahafo region and the Eastern region combined produce about 77.6%, 73.4%, 62.53%, 59.2% and 58.2% of total cocoyam, plantain, cassava, maize and yam production in the country respectively. It is also important to note that, three out of the four cereal crops (rice, millet and sorghum) produced in the country are predominantly produced in the three northern regions of the country with over half of rice production produced in these regions and millet and sorghum produced only in this part of the country (see Figure 2).

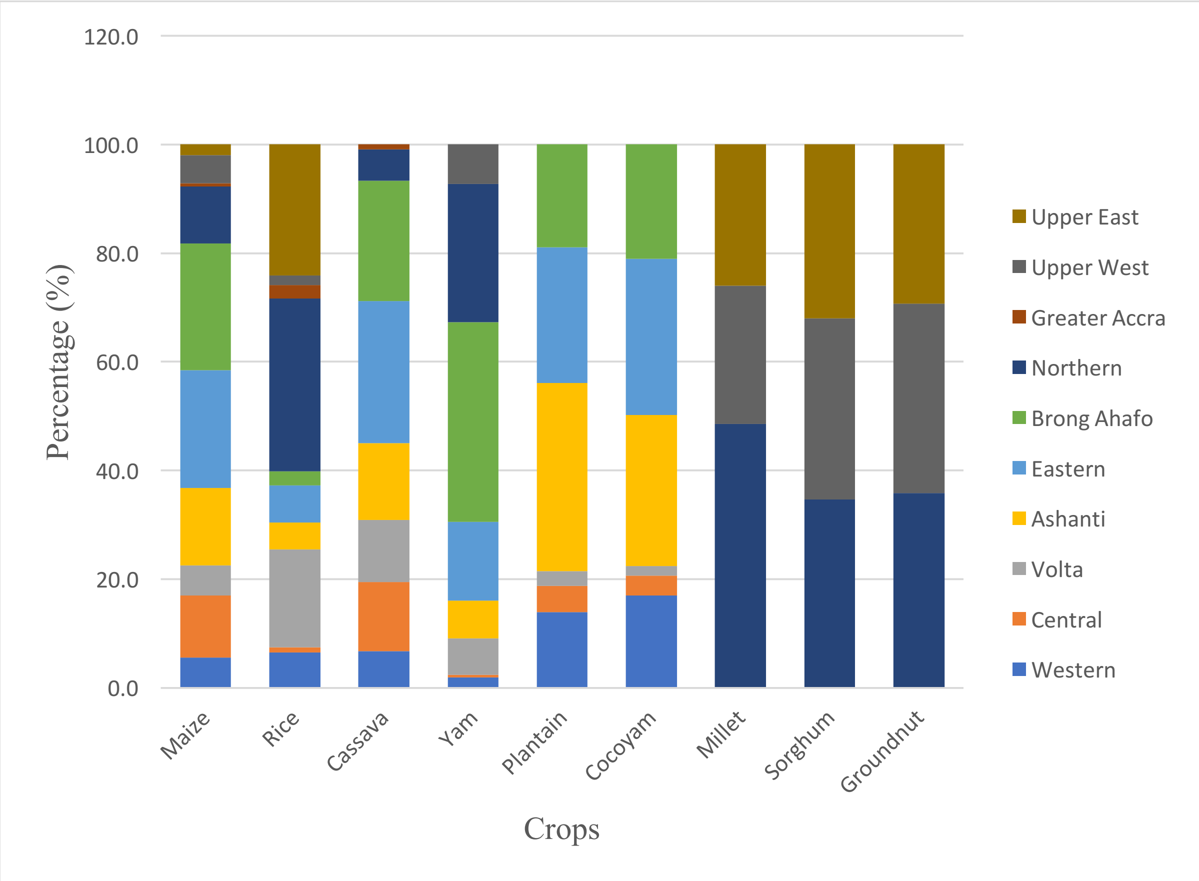

Fig. 2: Share of crop produced in different regions from 1990-2015.
Source: SRID of MOFA, 2016.

The descriptive statistics of crop yield, which is measured by the ratio of crop production and area cultivated for each crop in each region, is presented in Table 3. It can be observed that even though the Northern region has the largest share of rice production in the region, Greater Accra region has the largest share of rice production per hectare with an average of 4.637mt/ha followed by the Volta region with rice productivity of 3.086mt/ha. Thus, in terms of productivity, the two regions with the large amount of rice production (Upper East and Northern region) are ranked third and fourth in the country with average productivity of 2.46 and 2.204mt/ha respectively. This implies that Greater Accra region the and the Volta region, which have the largest per hectare production, are the most productive regions in terms of land used for rice production. However, it is less risky to produce rice in the Northern region than in the Greater Accra and Volta region because the northern region has the least amount of variation in yield (0.387mt/ha) compared with a variation of rice yield of 2.516mt/ha and 0.732mt/ha in the Greater Accra and Volta regions respectively. Also, even though the Brong Ahafo region has the highest mean productivity in maize, cassava and plantain in the country, it is less risky to produce these crops in other regions in the country. For example, it is less risky to produce maize and cassava in the Western region compared to production in the Brong Ahafo region. It is also less risky to produce plantain in the Eastern region, which has a variation in yield of 0.817mt/ha, compared to the variation in yield of 3.62mt/ha in the Brong Ahafo region. Yam and cocoyam were also found to be more productive in the Eastern region with an average productivity of 17.223 and 7.332mt/ha respectively. However, it is less risky to produce yam and cocoyam in in the Central and Western regions respectively compared to production in the other regions.

Table 3: Descriptive statistics of crop productivity by regions in mt/ha (1990-2015).

Crop		Western	Central	Volta	Ashanti	Eastern	Brong Ahafo	Greater Accra	Northern	Upper West	Upper East
Maize	Mean	1.366	1.549	1.521	1.406	1.801	1.845	0.953	1.223	1.472	1.196
	Std. Dev.	0.167	0.409	0.275	0.212	0.308	0.206	0.223	0.302	0.255	0.354
Rice	Mean	1.245	1.490	3.086	1.852	2.172	1.210	4.637	2.204	1.494	2.460
	Std. Dev.	0.062	0.455	0.732	0.632	0.710	0.422	2.516	0.387	0.443	0.722
Cassava	Mean	9.699	13.29	15.12	11.97	14.81	15.42	7.961	9.376		
	Std. Dev.	1.105	3.074	1.793	3.644	4.395	2.184	3.397	3.614		
Yam	Mean	6.921	5.242	12.07	11.91	17.22	14.94		11.40	13.70	
	Std. Dev.	1.271	0.517	2.144	2.673	1.564	3.045		3.500	3.333	
Cocoyam	Mean	5.878	4.822	6.081	7.317	7.332	6.497				
	Std. Dev.	0.347	0.522	1.524	1.614	0.885	1.002				
Plantain	Mean	8.286	6.864	6.575	9.119	9.052	9.772				
	Std. Dev.	1.220	1.486	1.012	1.364	0.817	3.620				
Millet	Mean								1.904	0.881	0.841
	Std. Dev.								1.609	0.173	0.211
Sorghum	Mean								1.154	1.028	0.971
	Std. Dev.								0.421	0.195	0.219
Groundnut	Mean								1.093	1.289	0.895
	Std. Dev.								0.439	0.235	0.148
Real Per	Mean	1250.1	1306.4	1251.7	1924.8	3206.4	3337.6	251.1	1795.7	2469.1	1092.8
Capita Income	Std. Dev.	574.01	807.83	626.99	1182.1	1669.5	1917.3	228.3	1026.0	1135.4	341.25
Annual Total	Mean	1904.1	1320.5	1381.9	1588.9	1596.8	1280.9	716.5	1083.8	1036.7	946.3
Rainfall	Std. Dev.	146.60	166.50	141.94	108.12	120.02	149.58	154.67	84.272	147.31	213.0
Avg. Annual	Mean	27.35	27.08	28.01	27.00	26.49	26.96	27.85	28.28	28.39	29.23
Temperature	Std. Dev.	0.278	0.337	0.274	0.630	0.266	0.446	0.422	0.279	0.332	0.322

Source: SRID of MOFA, 2016.

Trends in agricultural labour force over the last two and half decades are presented in Figure 3. As expected, the population of Ghana has been increasing in all regions of the country. The results of the trend in agricultural labour force shows that, the number of people engaged in agriculture in the Northern region has increased tremendously over the last one and half decade after being virtually constant in the 1990s. The Greater Accra region, which is the second most populous region in the country after the Ashanti region is the region with the least number of people engaged in agriculture. Agricultural labour force in the Ashanti region has been declining over the last two and half decades. However, the region still contributes the third highest number of people engaged in agricultural in absolute terms after Northern and Brong Ahafo regions.

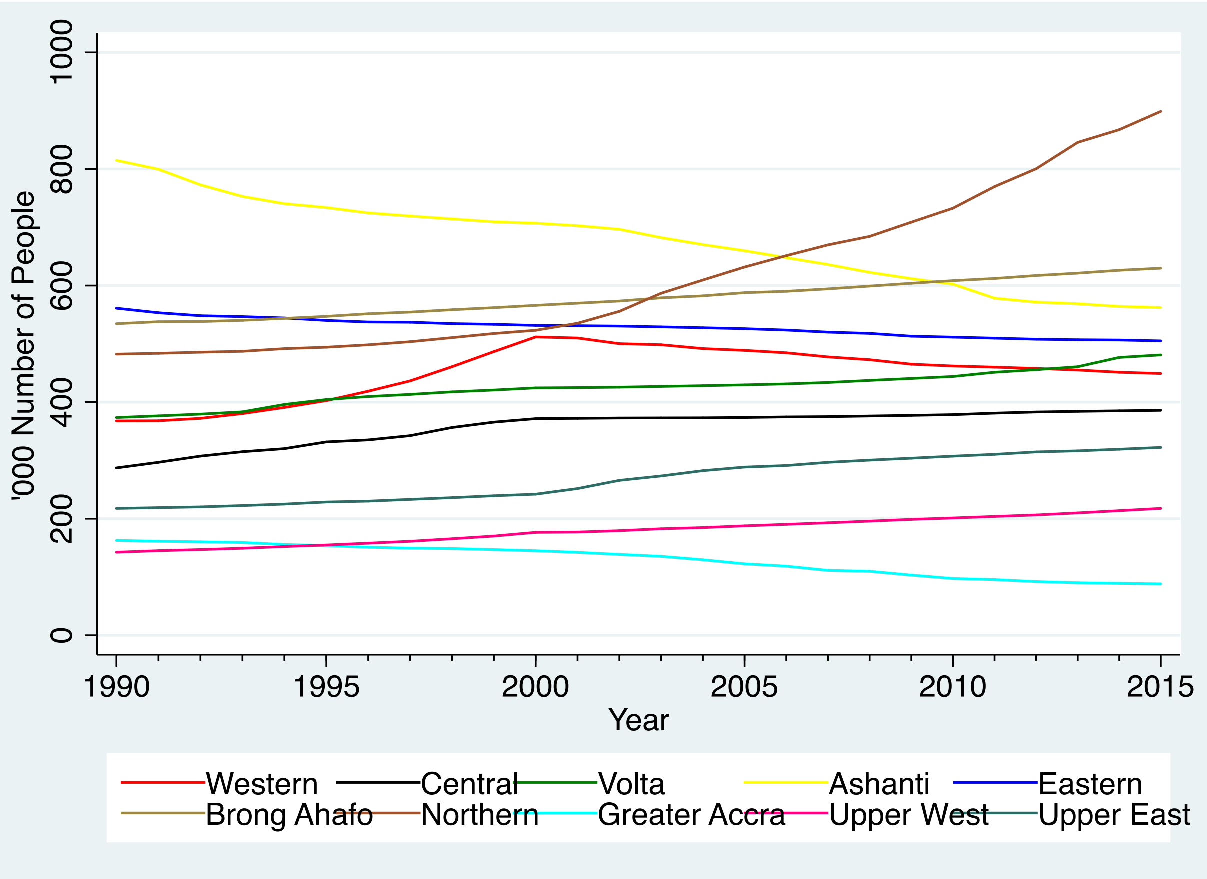

Fig. 3: Trends in regional population and agricultural labour force from 1990-2015.

The results on the real per capita income from crop production, which is measured by the ratio of real annual income to the agricultural labour force is presented in the bottom part of Table 3. The results show that the Brong Ahafo region earns the highest income per household with an average of GH¢3337.61 per year followed by the Eastern region, which earns an average of GH¢3206.44 real per capita income per year from crop production. Real per capita earnings in the Greater Accra region was very low compared to earnings in the other regions with an average of GH¢251.07 per year over the last two and half decades. The overall mean per capita income from crop production over the last two and half decade was GH¢1788.58 with a standard deviation of GH¢1411.45. The high standard deviations in all the regions indicates that purchasing power of income from crops have been highly variable over the years.

The climate variables are time series of annual precipitation and annual average temperature from 1990 to 2015. I used annual precipitation and annual average temperature in our analysis so as to be able to measure the impact of precipitation falling directly on crops (wet season precipitation) and the impact of inter-seasonal water accumulation on crop production (dry season precipitation). The summary statistics of annual precipitation and average annual temperature is provided Table 3. The results show that the Eastern region is the coolest region in the country with an average temperature of 26.49°C followed by the Brong Ahafo region and the Ashanti region, with an annual average temperature of 26.96°C and 27.0°C respectively. The hottest region in the country was found to be the Upper East region with an average temperature of 29.23°C. The West region has the highest amount of precipitation during the year with an average annual rainfall of about 1900mm. This is followed by the Eastern and Ashanti regions, which have an average of 1597mm and 1589mm per annum respectively over the last two and half decades. The Greater Accra region has the least amount of precipitation.

4. Methodology

The usual approach in modelling the relationship between productivity and inputs is based on the mean levels of inputs and outputs where the farmers' decision problem is solved by equating the marginal value of output to factor costs. It is, however, widely recognized that agricultural production is stochastic and the levels inputs used also influence higher moments of the distribution of outputs (Just and Pope, 1979; Antle, 1983). This stochastic nature of agricultural production is a major source of risk. Consequently, variability in productivity is not only explained by factors out of the control of the farmer such as climate change, input and output prices but also by controllable factors such as varying of the levels of inputs (Just and Pope, 1979; Antle, 1983). In effect, it has been shown that a risk averse farmer uses less (more) of a risk-increasing (risk-decreasing) factor than a risk neutral farmer. Risk, therefore has an important bearing on the production decisions of farmers as inputs selection does not only depend on their yield but also on their risk effects.

According to Hardaker et al. (1997), production decisions of farmers are also influenced by market risks, which are associated with the uncertainty about future prices of inputs and outputs and the reliability of input supplies. Therefore, even though market risks are essentially exogenous, farmers can affect the yield variability and the distribution of returns by the choice of inputs or the combination of inputs. In general, production risks have a tremendous impact on agriculture especially, the production patterns and supply behaviour of small holder farmers. Another form of risk that is not under the control of the farm can come from the changing climate. However, this risk can be minimized by the adoption of adaption strategies available to the farmer.

To be able to identify the risky variables that affect per capita income from crop production in Ghana, a stochastic production function developed by Just and Pope (1978) was employed. This production function is the sum of a deterministic component that relates to the level of yield, a stochastic component that relates to the variability in the level of yield and is represented by the equation below:

$$y_{it} = f(X_{it}, \beta) + h(Z_{it}, \alpha)^{0.5}\varepsilon_{it} \tag{1}$$

where y_{it} is the natural log of per capita income from crop production for region (i) at time (t), X_{it} are the independent variables including climate variables and Z_{it} may contain the same elements as X_{it}, ε_{it} is the stochastic term with zero mean and constant variance (σ_ε^2), β and α are parameters to be estimated. Per capita income from crop production is used as the dependent variable because it is the main source of livelihood for farmers (Schnitzer et al., 2014). I adopted the log-transformation of the per capita income from crop production as the dependent variable because the findings reported by Schlenker et al. (2006) suggests that a log-transformation outperforms a linear specification, since the distribution of income is non-negative and typically highly skewed.

The estimation of the first part of the above equation gives the average effect of the independent variables on per capita income, while estimating the second part of the equation gives the effect of each independent variable on the variance of per capita income (Chen et al., 2004). It is also important to note that increases and decreases in income variability as a result of change in the explanatory variables are determined by the sign of h_z (Chen et al., 2004). This is because the Just and Pope production function does not impose ex ante restrictions on the risk effects of inputs considered in the model. In effect, Z_{it} is said to be risk-increasing if it increases the variance of crop yield, that is $h_z > 0$, under uncertainty and decreasing otherwise. However, the variance function does not distinguish between upside or downside risk. In effect, following Antle (1983), I will also employ the third central moments (measuring skewness), which measures downside risk exposure. Therefore, the i^{th} input can be said to affect downside risk exposure through its effect on skewness. For instance, the i^{th} input would contribute to decreasing downside risk exposure when the differential of the third moment is greater than zero and vice versa. In particular, if the coefficient estimate of the i^{th} input of the skewness function is positive, it implies that input i contributes to decreasing downside risk exposure.

The Just and Pope Production function can be considered as an estimation with multiplicative heteroscedastic errors given as follows:

$$y_{it} = f(X_{it}, \beta) + \mu_{it} \tag{2}$$

where $\mu_{it} = h(Z_{it}, \alpha)^{0.5} \varepsilon_{it}$ is a disturbance term with zero mean and variance:

$$Var(\mu_{it}) \equiv \sigma_{\mu_{it}}^2 = \sigma^2 h(Z_{it}, \alpha)^2 \tag{3}$$

This production function has traditionally been estimated by the three-stage Feasible Generalized Least Squares (FGLS) approach. However, Saha et al. (1997) show that Maximum Likelihood Estimates (MLEs) are more efficient and unbiased than FGLS estimates for small samples in Monte Carlo experiments. The maximum likelihood method will be employed to estimate this model. This is because in other types of heteroscedastic model where the FGLS method is applied, the consistency of the estimates of α guarantees efficient estimate of β and hence little concern is given for the efficiency of α estimates (Chen *et al.*, 2004). Since this study will capture the risk effects of inputs, the efficiency of α estimates are very important. The likelihood function would therefore be:

$$L = \left[\frac{1}{2\pi}\right]^{N/2} \prod_{t=1}^{\tau} \prod_{i=1}^{n} \left[\frac{1}{h(X_{it}, \alpha)}\right]^{1/2} exp\left[\frac{-\{y_{it} - f(X_{it}, \beta)\}^2}{2h(X_{it}, \alpha)}\right] \tag{4}$$

where *n* is the number of zones and *τ* is the number of time periods and $N = n\tau$. The log-likelihood function would then be given by the expression below:

$$lnL = -\frac{1}{2}\left[N * \ln(2\pi) + \sum_{t=1}^{\tau} \sum_{i=1}^{n} ln[h(X_{it}, \alpha)] + \sum_{t=1}^{\tau} \sum_{i=1}^{n} \frac{\{y_{it} - f(X_{it}, \beta)\}^2}{h(X_{it}, \alpha)} \right] \tag{5}$$

Maximising this equation provides a maximum likelihood estimates of the parameter vectors β and α.

4.1 Panel Unit Root Test

The panel data estimation processes relate crop productivity to exogenous variables and this procedure results in estimates of the impact of the exogenous variables on levels and the variances of the output. It is assumed by the model that all the included variables are stationary, and hence deterministic and stochastic trends in variables can introduce spurious correlations between variables, as the errors in the data generating processes for different series might not be independent (Chen *et al.*, 2004). In effect, a positive trend existent in agricultural crop yields can be accounted for by introducing deterministic time trend. However, even after introducing the time trend the correlation between variables remains spurious. Therefore, testing for stationarity of the variables may help satisfy ideal conditions for the regression which will result in appropriate inferences. I, therefore, consider a simple panel data model with first order autoregressive component with

$$y_{it} = \rho_i y_{i,t-1} + M_{it}\gamma_i + \eta_{it} \tag{6}$$

Where y_{it} is the variable to be tested and η_{it} is a stationary error term. The term M_{it} can represent panel specific means, panel specific means and a time trend or nothing. The model can be rewritten as:

$$\Delta y_{it} = \phi_i y_{i,t-1} + M_{it}\gamma_i + \eta_{it} \tag{7}$$

where $\Delta y_{it} = y_{it} - y_{it-1}$ and $\phi_i = \rho_i - 1$ with a null hypothesis of $H_0{:}\, \phi_i = 0$ for all i (presence of panel unit root) versus the alternative hypothesis of no panel unit root ($H_a{:}\, \phi_i < 0$ for at least one i). The Fisher type panel unit root test proposed by Madalla and Wu (1999) which combines p-values of unit root test for each cross-section unit for test of unit root in panel data was adopted. This test was used because of its advantages over other test like the Im–Pesaran–Shin (see Maddalla and Wu, 1999; Choi, 2001) and it is also able to handle unbalanced panels. The decision rule for the Fisher type test is that the null hypothesis is rejected in favour of the alternative hypothesis, for at least one *i* at the significant level α when $P > c_{p\alpha}$, where $c_{p\alpha}$ is the upper tail of the chi-square distribution with 2N degrees of freedom (Choi, 2001).

The results of the Philip Perron (PP) Fisher panel unit root revealed that the total cropped area and the real per capita income from agriculture are stationary. All the other variables that are related to the climate were also found to be stationary (see Table 5).

Table 5: Unit Root Test Results with individual effects and individual linear trends.

Variable	**Statistics**	**p-value**
Real Per Capita Income	55.572***	0.0000
Total Cropped Area	138.688***	0.0000
Agricultural Labour Force	34.787**	0.0213
Climate		
Annual Average Temperature	46.211***	0.0008
Annual Precipitation	185.067***	0.0000
Variability in Average Temperature	170.012***	0.0000
Variability in Annual Precipitation	190.157***	0.0000

*** p<0.01, ** p<0.05, * p<0.1

To be able to estimate the model, we must specify the forms of the mean and variance functions explicitly. Following Isik and Devadoss (2006) and Palanisami *et al.* (2011), the following quadratic form is assumed for the mean function:

$$f(X_{it},\beta) = \beta_0 + \beta_1 A + \beta_2 A^2 + \beta_3 L + \beta_4 L^2 + \beta_5 t + \beta_6 t^2 + \beta_7 P + \beta_8 P^2 + \\ +\beta_9 T + \beta_{10} T^2 + \beta_{11} VP + \beta_{12} VT \quad (8)$$

where A is, the area cultivated for crops, which is used as a proxy for farmer's wealth and access to land, L is total regional agricultural labour force, *P* is precipitation, *VP* is variability in precipitation, *T* is temperature, *VT* is variability in Temperature, *t* is time, which is used as a proxy for change in technology, institutional changes and CO2 fertilization (Attavanich and McCarl, 2011). The variance function $\sigma_\varepsilon^2 h(Z_{it};\alpha,\eta)^2$ with $\sigma_\varepsilon^1 = 1$ was assumed to have an exponential form with

$$h(Z_{it},\alpha) = \exp(\alpha Z_{it}) = exp(\alpha_0 + \alpha_1 A + \alpha_2 A^2 + \alpha_3 L + \alpha_4 L^2 + \alpha_5 t + \alpha_6 t^2 + \\ + \alpha_7 P + \alpha_8 P^2 + \alpha_9 T + \alpha_{10} T^2 + \alpha_{11} VP + \alpha_{12} VT) \quad (9)$$

This form of variance function is developed by Harvey (1976) and is employed subsequently in several studies (Asche and Tveteras, 1999; Isik and Khanna, 2003; Isik and Devadoss, 2006; Palanisami et al., 2011). I also estimated linear forms for both the mean, variance skewness functions.

5. Empirical Results and Discussion

An important step that must be considered before the estimation is done is data exploration. To begin, I tested to find out whether heteroscedasticity was present in the models using a Breusch-Pagan test. The results show that the null hypothesis of constant variance should be rejected at 1 percent significant level for both the linear and quadratic models (χ^2 (1) = 24.6 and χ^2 (12) = 32.98). I also tested to find out, whether autocorrelation was present in the model or not by testing for autocorrelation by region. The Durbin-Watson test was used and the results show that the test was non-conclusive in almost all the regional models, except the Eastern region, the Brong Ahafo region and the Northern region where the null hypothesis of no autocorrelation was not rejected. I, therefore, estimate the models by correcting for heteroscedasticity by using the maximum likelihood estimation. In estimating the standard panel model, we must compare the random effects model with the fixed effects model. I prefer the fixed effects model to the random effects model for all of the estimation, because the regions are 'one of a kind' and cannot be viewed as a random draw from some underlying population. However, since the maximum likelihood method uses a random effects option for its estimation, the random effect method was adopted.

Before estimating the models, I presented the descriptive statistics of the explanatory variables used in the model in Table 6. The results show that on the average the total amount of land used to cultivate the 8 crops considered is about 3173.72 km^2, which is about 25 percent of the total land area used to cultivate annual crops in 2015 (MOFA, 2016). The results also show that, the average number of people engaged in agriculture over the last two and half decade was about 420790 per year. The average temperature and average total precipitation in Ghana are 27.66°C and 1285.63mm respectively.

The regression coefficients for the mean, variance and skewness of real per capita income from agriculture models (linear and quadratic functions) from the maximum likelihood estimation of the stochastic production function are presented in Table 7. The results of the mean per capita model for both the linear and quadratic forms showed expected signs in general. For instance, crop area cultivated, which is used as a proxy for farmer's wealth and access to land has a positive effect on per capita income from crops in the linear model, suggesting that an increase in the total land area by 1 unit will lead to an increase in per capita income by 0.0002%. Similar result was found in the quadratic model. In particular, the area cultivated had a concave relationship with per capita income from crops, indicating that investing more land in the production of these crops could increase the per capita income from these crops in general. However, as more and more land is invested, the gain in per capita income begins to diminish. This result confirms the general expectation that larger planting areas for a crop should lead to lower average production since more marginal and less suited land is then cultivated. In general, area cultivated was found to have a risk increasing effect on the variability in per capita income. However, it was found to contribute to decreasing downside risk exposure.

Table 6: Descriptive Statistic of Explanatory variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Total Area ('000)	317.37	177.63	10.82	1038.56
Total Area sq. ('000,000,000)	132.98	133.98	0.117	1078.62
Agric. Labour Force ('000)	420.79	185.05	88.22	898.79
Agric. Labour Force sq. ('000,000,000)	211.18	161.15	7.78	807.83
Trend	13.5	7.51	1	26
Trend sq.	238.5	209.03	1	676
Average Temperature	27.66	0.87	25.73	29.94
Average Temperature sq.	766.04	48.43	661.79	896.6
Annual Precipitation	1285.63	365.56	366.4	2176.7
Annual Precipitation sq. ('000)	1785.92	956.92	134.25	4738.02
Variability in Temp.	2.25	1.33	0.39	7.52
Variability in Precipitation ('000)	7.79	3.75	1.09	25.2

The number of people engage in agriculture was found to have a significant negative effect on real per capita income, which in general implies that agriculture labour force grows slightly faster than the growth in agriculture income in general. That is, an increase in agricultural labour force leads to a less than proportionate increase in agricultural income. In effect, encouraging more individuals to engage in agriculture without making efforts to improve the growth in income from agriculture will not be a very productive policy. Increases in agricultural labour force was also found to have a significant risk-decreasing effect on the variability in real per capita income but contribute to increasing downside risk exposure.

The trend variable is usually interpreted as the effect of technology and/or institutional changes on crop production (Chen *et al.*, 2004; Isik and Devadoss, 2006; McCarl *et al.*, 2008; Palanisami *et al.*, 2011). However, this may generate incorrect estimates of the real effect of technological change on crop yield since atmospheric CO2 is also a potential key driver of potential yield impacts. Since it is difficult to unravel the difference between time and CO2 effects because of the perfect collinearity between time and atmospheric CO2 plus the small variation of atmospheric CO2 concentration across locations (Attavanich and McCarl, 2011), our time trend variable will implicitly capture both the effects of CO2 fertilization, technological progress and/or institutional changes and improvement in the accessibility of market.

The results show that, the trend variable has a significant positive effect on real per capita income from food crop production in Ghana, in general. This confirms the results of Chen *et al.* (2004), Isik and Devadoss (2006), McCarl *et al.* (2008) and that of Palanisami *et al.* (2011), who found that improved technology augments both the mean and variability of crop yield. This implies that real per capita income continues to increase as technology continues to progress and there are more effective institutional changes and also as a result of increasing atmospheric CO2 fertilization. This is because the negative effect of the square of trend in the quadratic model was statistically insignificant. In effect, I can conclude that technology advancement and more improvement in institutions can help improve the per capita income from crop production. Even though, the trend variable, which is used as a proxy for technology advancement, institutional changes and increasing atmospheric CO2 fertilization, has a significant positive effect on the mean of per capita income, the results show that it has a risk increasing effect on the variability of per capita income. The results also show shows that trend has a positive effect on the skewness of real per capita income and thereby contributes to decreasing downside risk exposure. This implies that technology advancement, institutional changes and atmospheric CO2 fertilization reduces the probability of crop failure resulting in increasing real per capita income.

Table 7: ML Estimated Coefficients from Mean, Variance and Skewness Function Regressions

Variables	Linear Model			Quadratic Model		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Area	2.0e-06***	5.7e-07***	8.6e-07***	0.007***	0.002***	0.003***
	(2.5e-07)	(4.5e-09)	(6.7e-09)	(0.001)	(2.6e-05)	(4.0e-05)
Area Sq				-0.005***	-0.001***	-0.002***
				(0.001)	(2.46e-05)	(3.69e-05)
Agric Lab	-7.3e-07**	-2.1e-07***	-3.2e-07***	-0.005***	-0.002***	-0.002***
	(3.3e-07)	(4.9e-09)	(7.3e-09)	(0.001)	(3.3e-05)	(5.0e-05)
Agric Lab sq.				0.004***	0.001***	0.002***
				(0.001)	(2.9e-05)	(4.4e-05)
Trend	0.057***	0.016***	0.0240***	0.058***	0.0190***	0.029***
	(0.003)	(7.7e-05)	(0.0001)	(0.011)	(0.0004)	(0.001)
Trend sq.				-0.0003	-0.0002***	-0.0002***
				(0.0003)	(1.3e-05)	(1.9e-05)
Avg Temp.	0.06	0.017***	0.026***	4.778***	1.405***	2.107***
	(0.059)	(0.001)	(0.002)	(1.551)	(0.058)	(0.087)
Avg Temp. sq.				-0.086***	-0.025***	-0.038***
				(0.029)	(0.001)	(0.002)
Rainfall	-0.0001	-3.1e-05***	-4.7e-05***	-0.0004	-9.4e-05***	-0.0001***
	(0.0001)	(2.8e-06)	(4.1e-06)	(0.0004)	(1.5e-05)	(2.3e-05)
Rainfall sq.				5.3e-05	5.6e-06	8.4e-06
				(0.0002)	(5.5e-06)	(8.3e-06)
Var. Temp.	0.029	0.008***	0.012***	0.017	0.003***	0.005***
	(0.030)	(0.001)	(0.001)	(0.029)	(0.001)	(0.002)
Var. Rain	-6.1e-06	-1.7e-06***	-2.6e-06***	-0.008	-0.003***	-0.004***
	(7.8e-06)	(2.0e-07)	(3.0e-07)	(0.007)	(0.0003)	(0.0004)
Constant	4.501***	3.167***	4.751***	-59.36***	-15.63***	-23.45***
	(1.671)	(0.028)	(0.042)	(21.11)	(0.794)	(1.191)
Sigma_u	0.618***	0.0004	0.001	0.625***	0.006***	0.008***
	(0.149)	(0.0016)	(0.002)	(0.172)	(0.002)	(0.003)
Sigma_e	0.271***	0.007***	0.011***	0.242***	0.010***	0.014***
	(0.012)	(0.0003)	(0.001)	(0.011)	(0.0004)	(0.001)
Observations	260	260	260	260	260	260
Number of id	10	10	10	10	10	10

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

With regard to the climate variables, I found out that annual precipitation has a no significant correlation on the real per capita income. However, the results show that precipitation has a negative significant effect on the variability in real per capita income. This implies that precipitation can be considered as a risk decreasing input in the production of crops. The results also show that precipitation has a significant negative effect on the skewness of real per capita income from crops, indicating that precipitation increases the probability of crop failure resulting in low real per capita income.

Real per capita income from crop response to average temperature was found to be concave. This implies that rising average temperature increases real per capita income from crops. However, this increase in real per capita income begins to diminish as average temperature continuous to rise above a maximum threshold of 27.78°C. This confirms the findings of USGCRP (2009), which states that, crops tend to grow faster in warmer conditions in general, and the effect of increased temperature for any particular crop depends on the crop's optimal temperature for the crop’s growth and reproduction. Therefore, rising average temperature can result in increased productivity of a crop depending on the area. It is however, argued that, if warming exceeds a crop's optimum temperature, productivity can decline (USGCRP, 2009).

The results also show that average temperature has a concave relationship with the variation in real per capita income from crops. This implies that below a certain threshold maximum temperature (27.78°C), rising average temperature has a risk increasing effect on the variability in real per capita income from crops. However, above this maximum threshold, rising temperature tends to have significant risk decreasing effect on the variability in real per capita income. The effect of temperature on the skewness of real per capita income was also concave, suggesting that below the maximum threshold of 27.78°C, rising average temperature reduces the probability of crop failure and thereby increasing real per capita income from crops. However, above this maximum threshold, rising average temperature increases the probability of crop failure and, thus, reduces real per capita income from crops.

Both variability in precipitation and temperature do not have any significant effect on real per capita income from crops. They, however, have a differentiated effect on the variance and skewness of real per capita income. In particular, variability in average temperature was found to have significant positive effect on both the variance and skewness of real per capita income, whereas variability in annual precipitation was found to have significant negative effect on the variance and skewness of real per capita income. This implies that, whereas variability in average temperature has a risk increasing effect on real per capita income, variability in annual precipitation was found to have a risk decreasing effect on real per capita income. Also, whereas variability in average temperature was found to reduce the probability of crop failure, variability in annual total precipitation was found to increase the probability of crop failure and thus reduces real per capita income.

6. Summary and Conclusion

Risk and uncertainty are ubiquitous and varied within the agricultural sector in both developed and developing countries, and even though the sources and consequences may differ between countries they are generally experienced by most farmers in most countries. For instance, crop production in Ghana is risky as it is mainly rain-fed and prone to a number of shocks including: climatic shocks, pest and diseases, bushfires and price shocks (Choudhary et al., 2015). According to Rosenzweig and Binswanger (1993), while several factors contribute to household income variability, rainfall variability is likely to influence welfare the most, particularly because it is spatially covariant. Barret et al. (2007) also argues that, weather risks and climate shocks are critically important constraints to wealth accumulation, particularly for those in rural areas who are either engaged in agricultural activities or have their livelihoods tied to the well-being of the farming sector.

In effect, before we institute policies to whether adapt or mitigate the effects of climate shocks on income from crop production and the effectiveness of policies to reduce these impacts, this study investigated how climate variability and other agricultural inputs affect real per capita agricultural income by using an econometric model to estimate a stochastic production function that quantifies the effects of these variables on the mean, variance and skewness of real per capita income from 9 food crops produced in the country.

The descriptive analysis of cropped area revealed that the total area cultivated has increased by about 16 percent over the last decade. It was, however, shown that the land area used to cultivate crops in the Greater Accra and Upper East regions has declined over the last decade. These two regions are also the regions with the lowest per capita income from agriculture in the country. The descriptive analysis of climate variables also revealed the Eastern region to be the coolest region in the country with the three northern regions being the hottest regions. The Volta region was also found to be the hottest region in the southern part of the country. The region with the highest amount of precipitation during the year is the Western region.

The results show that trend variable, which is usually interpreted as the effect of technology and/or institutional changes, market access and CO2 fertilization on crop production in the literature, was found to have a significant positive impact on real per capita income from crop production. It was also revealed that, even though trend has a risk increasing effect on the variability of real per capita income, it reduces the probability of crop failure resulting in increasing real per capita income. Crop area cultivated, which is used as a proxy for farmer's wealth and access to land was also found to have significant concave relationship with real per capita income from crop production, indicating that investing more land in the production of food crops could increase the per capita income from crops in general but as more and more land is invested, the gain in per capita income begins to diminish. Area cultivated was also found to contribute to decreasing downside risk exposure. The number of people engage in agriculture was found to have a significant negative effect on real per capita income, which in general implies that agriculture labour force grows slightly faster than the growth in agriculture income in general.

One major finding of this study was the effect of annual average temperature on real per capita income from crops, which was found to be significantly concave. This implies that rising average temperature increases real per capita income. However, the increase in real per capita income diminishes as average temperature increases above a maximum 27.78°C. The results also show that rising temperature has a risk increasing effect on the variability in real per capita income below this maximum threshold and a risk decreasing effect otherwise. It was also revealed by the results that rising average temperature reduces the probability of crop failure and thereby increasing real per capita income from crop below the maximum threshold. However, above this maximum threshold, rising average temperature increases the probability of crop failure and thus reduces real per capita income from crops. The results also show that annual precipitation has no significant correlation with the real per capita income. It was, however, found to have a risk decreasing effect on the variability in real per capita income but increases the probability of crop failure resulting in low real per capita income.

Both variability in precipitation and temperature do not have any significant effect on the level real per capita income from crops. However, whereas variability in average temperature has a risk increasing effect on real per capita income, variability in annual precipitation was found to have a risk decreasing effect on real per capita income. Also, whereas variability in average temperature was found to reduce the probability of crop failure, variability in annual total precipitation was found to increase the probability of crop failure and thus reduces real per capita income. Therefore, future research will focus on how different degree of exposure to the risk flood, which is caused by variation in precipitation, impact on the behavioral traits of farmers and their decision-making process in adopting adaptation strategies.

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Economic Preferences and Adaptation to Natural Risk: Experimental Evidence from Ghana

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Abstract

Contrary to standard economic hypothesis that individuals' preferences are fixed, a growing body of research indicates that there is an endogenous link between individuals' living environment and their economic preferences. This study investigates whether risk preferences, time preferences, social cooperation and loss aversion reacts to the environment by means of a field experiment in rural Ghana. In particular, this study exploits a natural experiment implied by different degree of exposure to risk in terms of flood and the effects these risks have on the behavioural traits of farmers, and their willingness to adopt adaptation strategies. The results show that preferences are not stable, with exposure to risks making people more risk averse, impatient and more cooperative. Even though each behavioural trait has a significant effect on adoption of adaptation strategies, only risk preferences are significant when all economic preferences are assessed together, indicating that risk preferences have a strong and significant effect on adaptation strategies. Also, exposure to different degree of risk has a significant effect on adaptation strategies, but the main channel through which it impacts respondents' adaptation decisions is through risk aversion. In particular, being exposed to high degree of risk makes respondents less likely to access credit to invest in their farms, more willing to pay higher agricultural insurance premium and more willing to contribute higher amount for the construction of drainage systems to reduce the impact of flood on their farms and households. In effect, by reducing the exposure to risk, policy makers can obtain less risk averse households and thereby making it easier to implement adaptation strategies.

1. Introduction

Risk and uncertainty play a significant role in almost every important economic decision. The extent to which people are willing to undertake decisions with uncertain outcomes constitutes their economic preferences. Therefore, assessing and measuring the economic preferences of individuals is critical for economic analysis and policy prescriptions (Charness et al., 2013). For example, risk preference is identified as one of the main drivers of farm management and land use decisions (Chavas et al., 2010; Jin et al., 2015) and, also, plays a major role in agricultural production decision (Feder, 1980; Just and Zilberman, 1983; Adger et al., 2009). Available research indicates that risk aversion inhibits the use of new, productivity increasing technologies and inputs such as improved seeds and fertilizers (Feder et al, 1985; Rosenzweig and Binswanger, 1983; Knight et al., 2003; Engle-Warnick et al. 2011; Dercon and Christiaensen, 2011; Liu 2013; Verschoor et al., 2016).

Previous studies assumed the interaction between economic preferences and the environment to be stable and then examined how a change in risk constraints induces a behavioural change. Contrary to this standard economic hypothesis that individual's preferences are stable, a growing body of research indicates that there is an endogenous link between individuals living environment and their economic preferences. For instance, Eckel et al. (2009) reported that individuals affected by hurricane Katrina exhibited significant risk loving behaviours. Other studies also suggest that preferences endogenously change with external cues such as market arrangements (Palacios-Huerta and Santos, 2004), civil war shocks (Voors et al., 2012), tsunamis (Callen, 2015), earth quakes (Cameron and Shah, 2012) and volcanic threats (Ali Bchir and Willinger, 2013). The results of these studies indicate that individuals' preferences are partly influenced by their social, institutional or natural environment.

The effect of the environment on preferences can be linked to background risk, which states that the presence of risks that cannot be avoided or insured against may make individuals less tolerant towards other, avoidable risks (Pratt and Zeckhauser, 1987; Kimball, 1993; Eekhoudt et al., 1996). It is worth noting that, before Eckel et al. (2009), the link between background risk and preferences was mainly focused on financial decisions (Guiso et al., 1996; Heaton and Lucas, 2001; Guiso and Paiella, 2008), and in the laboratory (Harrison et al., 2007; Lee, 2008; Lusk and Coble, 2008). To the best of our knowledge, Eckel et al. (2009) were the first to use field experiments to establish the link between a natural disaster (hurricane Katrina in US) and individuals' economics preference. Surprisingly, their results indicate that respondents affected by Katrina exhibit risk-loving behaviour. The emotional state of respondents was indicated as the reason for this result.

However, researchers are yet to build a consensus on how economic preferences vary with different exposure to background risk, with different research having contrasting results. For example, while Cameron and Shah (2012) reported that respondents exposed to flood and earthquake in Indonesia exhibit higher levels of risk aversion compared to unexposed respondents, Ali Bchir and Willinger (2013) reported that there was no significant effect on households exposed to volcanic threats on risk preferences. Voors et al. (2012) also reported that shocks such as flood and drought do not have significant impact on risk preferences but conflicts make respondents more risk seeking. A study by Reynaud and Aubert (2013) also suggest that villages in Vietnam affected by a flood in recent years exhibit more risk aversion in the loss domain. On the effects of the environment on time preferences, whereas Callen (2015) revealed that Sri Lankan workers affected by tsunami in 2004 were more patient, Ali Bchr and Willinger (2013) report that poor households in villages exposed to volcanic threats in Peru exhibit more impatient behaviours.

Economic preferences have often been measured in advanced countries in the lab with not so much being done in the field in developing countries, and thus making it important to assess preferences in developing countries. Risk and uncertainty are predominant in agriculture, which plays a dominant role in the livelihoods of households in developing countries, serving as a stimulus for economic growth, providing food security and assisting in poverty reduction. However, in Sub-Saharan Africa, poverty and food insecurity are critical issues for most countries with one of the major cause of these problems attributed to agriculture's susceptibility to production, price and policy risks which impact farmers' income and welfare (Cervantes-Godoy et al., 2013; Ellis, 2017). It is also important to assess economic preferences in developing countries because preferences among farmers have been identified as important constraints that keep farmers from reaching their productive potential. For example, poor households in developing countries are reluctant to invest in new technologies because of risk aversion and high impatience levels (Yesuf and Bluffstone, 2009; Tanaka et al., 2010). Boucher et al. (2008) also argue that some farmers in Peru are not willing to access formal credit market, even if it would help raise their productivity and income levels because of risk aversion. Furthermore, Carter and Barrett (2006) argue that risk aversion may lock poor agricultural households in poverty traps.

In addition, it is easy to find different degree of exposure to extreme conditions in developing countries. For example, climate shocks, which include erratic rainfall, increases the risks faced by farmers by negatively affecting yields of most crops in developing countries (Nelson et al., 2009). This climate shock is ranked among the most pervasive stresses that rural households face (Ziervogel and Calder, 2003), especially in developing countries where rural livelihoods are inextricably linked to the natural environment (Mensah and Adu, 2015). However, the risks posed by the consequences of climate shock can be lowered by adaptation, which is considered the most important policy option in reducing the impact of climate shock (IPCC, 2014). Adaptation strategies involves changes in agricultural management practices in response to changes in climate conditions and it often involves a combination of various individual responses at the farm-level and assumes that farmers have access to alternative practices and technologies available in the region. However, most of these strategies are characterised by risk and uncertainty, which makes it more prudent to understand the link between farmers' preferences and how they respond to new programs that are crucial for policymakers in reducing the impact of natural shocks on households.

This study will, therefore, test in a clean way by means of a field experiment, using a between subject design, not only replicating Cameron and Shah (2012) and Ali Bchir and Willinger (2013) on the effects of exposure to risk on risk and time preferences, but also loss aversion and cooperation. To the best of my knowledge, this is the first paper that investigates how preferences react to different degree of exposure to risk in a between subject design investigating a large spectrum of preferences. In particular, it is the first paper investigating the link between exposure to risk and cooperation. This would be done by exploiting a natural experiment implied by exposing respondents to different degree of risk in terms of flood and the effects this risk have on the behavioural traits of the respondents. In effect, communities that are highly prone to the risk of flood would be considered as our treated group and the least susceptible to flood communities considered as our control group.

This study would also be used to investigate how economic preferences influence households' decision-making process in adopting adaptation strategies. A total of four adaptation strategies were considered but only three of them, which include willingness to access credit, willingness to pay for agricultural crop insurance and willingness to pay for a drainage system, were analysed. Farmers' willingness to pay for fertilizers was not included in the analysis because I perceived that respondents who are in the treated group will be less likely to pay high amount for fertilizers. Indeed, the results show that there are highly significant differences in the willingness to pay for fertilizers between the two groups. On the willingness to pay for drainage systems and fertilizers, respondents were asked to indicate how much they would be willing to sacrifice in monetary terms in order to reduce the impact of climate shocks on their households and farms by paying for drainage systems and fertilizers. In all, a dichotomous contingent valuation method (CVM) with follow up questions, which is used to reduce strategic biases in CVM, was used. In the case of households' willingness to access formal financial credit and purchase of agricultural insurance, an initial decision on whether to access credit and purchase insurance was asked and a subsequent decision on the maximum amount respondents are willing to access as credit and the maximum willingness to pay as insurance premium conditional on a positive initial decision was determined.

The results show that economic preferences are not stable, with different degree of exposure to risk having significant impact on individual's risk preferences, impatience level and cooperation. In particular, the results show that exposure to risk makes people more risk averse, more impatient and more cooperative. Respondents in this study exhibited strong degree of risk aversion in general, contradicting the results of Vieider and L'Haridon (2016), which indicates that subjects in developing countries are generally less risk averse. However, more risk aversion behaviour of respondents in this study may be as a result of the fact that both the treated and control groups are exposed to some degree of background risk, thereby making the whole sample more risk averse and confirming the theory of the relationship between background risk and risk preferences (Cameron and Shah, 2012). Also, exposure to high degree of risk has a significant effect on adaptation strategies, but the main channel through which it impacts respondents' adaptation decisions is through risk aversion. In particular, the results show that being exposed to high degree of risk makes respondents less likely to access credit to invest in their farms, more willing to pay higher agricultural insurance premium and more willing to contribute higher amount for the construction of drainage systems to reduce the impact of flood on their farms and households.

The outline of the paper is as follows. The second section looks at the conceptual framework where I summarize the experimental tasks used to elicit economic preferences. The experimental design and procedure are summarized in the third section, while the methodology used to analyse the results is presented in the fourth section. The fifth section presents the results of the paper and the sixth section concludes the paper.

2. Conceptual Framework

There are two broad approaches identified in the literature for eliciting economic preferences of individuals: survey and experimental methods (Charness et al., 2013). Whereas, the survey method uses questionnaire to elicit risk preferences by asking individuals about personal traits that are directly related to risk aversion (Cesarini et al., 2009; Couture et al., 2010; Charness and Viceisza, 2016; Dohmen et al., 2011) and impatience levels (Atmadja, 2008; Ubfal, 2016), the experimental approach uses experiments to observe the choices of subjects that reflect each individual's risk (Gneezy and Potters, 1997; Holt and Laury, 2002; Eckel and Grossman, 2008; Crosetto and Filippin, 2013) and time preferences (Coller and Williams, 1999). The major drawback of the survey method is that, questionnaires are typically not directly incentivized and thus raises questions about whether the elicited risk preferences reflect an individual's true attitudes toward risk (Charness et al., 2013). The experimental approach solves this problem by designing experiments where many of the experimental factors are controlled by the experimenter and thus ensuring that the elicited risk measure is influenced only by the individuals' risk (Jin et al., 2015) and time preference.

Economic field experiments exploring economic preferences in both developed and developing countries have a long tradition. Most studies assumed the interaction between economic preferences and the environment to be stable. However, more recent studies have shown that there is an endogenous link between individuals' economic preferences and their living environment. Most of these studies have often being done in the lab and developed countries (Beaud and Willinger, 2012; Herberich and List, 2012; Eckel et al., 2009; Lee, 2008; Lusk and Coble, 2008; Harrison et al., 2007) with only a few being done in developing countries (Ali Bchr and Willinger, 2013; Voors et al., 2012; Cameron and Shah, 2012). In this study, I contribute to the literature by not only replicating Cameron and Shah (2012) and Ali Bchir and Willinger (2013) on the effects of exposure to risk on risk and time preferences, but also on loss aversion and cooperation. This will help in investigating how preferences react to different degree of exposure to risk in a between subject design investigating a large spectrum of preferences. In this section, I look at the conceptual framework, which summarizes the experimental tasks used to elicit economic preferences used in this study.

2.1 Risk Preferences

The expected utility theory states that a rational individual chooses between risky or uncertain prospects by comparing their expected utility values. In other words, the theory of expected utility is the weighted sums obtained by adding the utility values of outcomes multiplied by their respective probabilities (Mongin, 1998). That is,

$$EUT = \sum_{i=1}^{n} p_i u(x_i) \tag{1}$$

where $u(x_i)$ is the level of utility derived from the final wealth which occurs with probability p_i for each of the *n* possible outcomes. When the utility function is concave, the individual is said to be risk averse, preferring a sure income of x_i to a fair gamble with expected value of x_i. Arrow (1965) and Pratt (1964) measure risk aversion as $r(x) = -\frac{u''(x)}{u'(x)}$, where the risk averse individual is represented by $r(x) > 0$, the risk preferring individual by $r(x) < 0$ and the risk neutral individuals by $r(x) = 0$.

Several approaches have been used to estimate the risk aversion of subjects. Most of these techniques are incentivised, although non-incentivised questions have also been used successfully in recent years. Also, some researchers favour the theoretical elegance of more sophisticated approaches, whereas others prefer the simpler approaches on the basis of the ease of comprehension and the greater probability of obtaining meaningful responses. The most commonly used risk elicitation technique in the literature is the multiple price list (MPL), which was first used by Binswanger (1980) to elicit risk preferences of farmers in rural India and later used by other researchers to price commodities (Kahneman et al., 1990) and elicits discount rates (Coller and Williams, 1999). However, the method was popularised by Holt and Laury (2002) to estimate risk parameters of a utility function (see Andersen et al., 2006 for a complete review of the model).

The MPL is a standard format, whereby subjects are provided with a fixed array of paired lottery options and asked to choose one option per pair (see Table 1). One main advantage of MPL design is that it can be explained to subjects and implemented with relative ease and also promotes honest answers (Andersen et al., 2006). However, Charness and Viceisza (2016) reported that this mechanism does not induce sensible and realistic choices among rural households citing low level of understanding of the method as the main problem.

Table 1: The ten-paired lottery-choice decisions of the MPL.

	Option A	Option B	Option A	Option B
1	1/10 of $2, 9/10 of $1.6	1/10 of $3.85, 9/10 of $0.1	☐	☐
2	2/10 of $2, 8/10 of $1.6	2/10 of $3.85, 8/10 of $0.1	☐	☐
3	3/10 of $2, 7/10 of $1.6	3/10 of $3.85, 7/10 of $0.1	☐	☐
4	4/10 of $2, 6/10 of $1.6	4/10 of $3.85, 6/10 of $0.1	☐	☐
5	5/10 of $2, 5/10 of $1.6	5/10 of $3.85, 5/10 of $0.1	☐	☐
6	6/10 of $2, 4/10 of $1.6	6/10 of $3.85, 4/10 of $0.1	☐	☐
7	7/10 of $2, 3/10 of $1.6	7/10 of $3.85, 3/10 of $0.1	☐	☐
8	8/10 of $2, 2/10 of $1.6	8/10 of $3.85, 2/10 of $0.1	☐	☐
9	9/10 of $2, 1/10 of $1.6	9/10 of $3.85, 1/10 of $0.1	☐	☐
10	10/10 of $2, 0/10 of $1.6	10/10 of $3.85, 0/10 of $0.1	☐	☐

Source: Holt and Laury, 2002.

Another risk elicitation method found in the literature is the one proposed by Gneezy and Potters (1997), which provides a measure of risk preferences in the context of financial decision making with real monetary payoffs. In this approach, a decision maker receives a certain amount of money and is asked to choose how much of it she wishes to invest in a risky option and how much to keep. The amount invested has a positive expected return. The subject keeps the amount of money not invested (see Gneezy and Potters, 1997; Haigh and List, 2005; Apicella et al., 2008; Charness and Gneezy, 2012). This method is relatively simple and can be implemented with one trial and basic experimental tools. Results from rural Senegal were in line with previous studies in developed countries (Charness and Viceisza, 2016). However, this method is not able to differentiate between risk neutral and risk loving individuals. Eckel and Grossman (2002) also developed explicitly a simple elicitation technique to elicit risk preferences that produced low heterogeneity in choices. In this method, participants were presented with a number of gambles and were asked to choose the one that they would like to play (see Table 2). The number of gambles presented to subjects vary (see Eckel and Grossman, 2008; Dave et al., 2010; Reynaud and Couture, 2012). The method is relatively easy for individuals to understand. However, it also cannot differentiate between different degrees of risk-seeking behaviour.

This paper would use a choice-based elicitation method developed by Crosetto and Filippin (2013) known as the Bomb Risk Elicitation Task (BRET). This task asks subjects to decide at which point to stop collecting a series of 100 boxes of which one contains a time bomb from a minefield. In other words, out of these 100 boxes are 99 empty boxes, which contains actual money, and one box, which contains a time bomb programmed to explode at the end of the task after all choices have been made. In particular, participants are asked to choose a number k ∈ [0, 100] that corresponds to the number of boxes they want to collect from the minefield, starting from the first box. Earnings to the participants increase linearly with the number of boxes collected (k). After all choices have been made, participants would then be asked to pick a number b ∈ [1, 100] from an urn that represents the position of the time bomb. If $b \leq k_i$, it means that participant i collected the bomb which explodes and wipes out his/her entire earnings. However, if $b > k_i$, then participant i leaves the minefield without the bomb and leaves with γ dollars cent for every box collected.

Table 2: Different gamble choices with alternative framing by Eckel and Grossman.

Gamble Choice	Event	Probability (%)	Loss Framing ($)	No-Loss Framing ($)
1	A	50	10	16
	B	50	10	16
2	A	50	18	24
	B	50	6	12
3	A	50	26	32
	B	50	2	8
4	A	50	34	40
	B	50	-2	4
5	A	50	42	48
	B	50	-6	0

Source: Eckel and Grossman, 2002.

Decisions by participants can be formalised as the choice of their favourite among the lotteries which summarise the trade-off between the amount of money that can be earned and the likelihood of obtaining it. The task amounts to choosing the preferred option among 101 lotteries which is fully described both in terms of probabilities and outcomes by a single parameter $k \in [0, 100]$.

$$L = \begin{cases} 0 & \frac{k}{100} \\ \gamma k & \frac{100-k}{100} \end{cases} \tag{2}$$

The expected value of these lotteries equals to $\gamma(k - 0.01k^2)$, which is a bow-shaped function with a maximum at $k = 50$ and trivially equal to zero for $k = 0$ and $k = 100$. If we normalise $u(0) = 0$, an individual who maximises his expected utility is expected to choose:

$$k^*: \frac{u(k)}{u'(k)} = 100 - k \tag{3}$$

Assuming the classic constant relative risk aversion (CRRA) utility function $u(x) = x^r$:

$$k^* = 100\frac{r}{1+r'} \tag{4}$$

This implies that a risk neutral subject would choose $k^* = 50$ and the implied levels of r for every possible choice k lies in the interval [0, 68.275] (see Crosetto and Filippin, 2013 Appendix A).

The BRET approach was used because it requires low numeracy skills and thus making it more useful for our subjects, who are rural farmers and mostly not formally educated, than other elicitation approaches like the MPL. The BREt also allows for the precise estimation of both risk aversion and risk seeking and thus generating a virtually continuous distribution of outcomes. Thus, the BRET is also more suitable for our subjects than both Gneezy and Potters (1997) and Eckel and Grossman (2002) approaches. Unlike other well-known elicitation approaches in the literature, BRET does not suffer from loss aversion as a potential confounding factor because it is entirely defined in a gain domain and does not even provide endogenous reference points against which some outcomes could be perceived as losses (Crosetto and Filippin, 2013). It can be performed even with paper and pencil and thus making it possible to be used in a field experiment. In section 3, I will present a version of the task which has been used to elicit preferences of 5 year olds children. This is because it is much simpler to understand considering the high illiteracy rate of our sample.

2.2 Loss Aversion

Traditionally, utility measurement has assumed that people behave according to expected utility. However, evidence abounds that people violate expected utility in systematic ways (Starmer, 2000) and that utility measurements based on expected utility give inconsistent results (Hershey and Schoemaker, 1985; Bleichrodt et al., 2001; Abdellaoui et al., 2007). It is also argued that there are two important causes of the violation of expected utility theory. They are the probability weighting, which is the nonlinear evaluation of probabilities, and the concept of loss aversion, which involves the finding that people evaluate outcomes as gains and losses relative to a reference point and are more sensitive to losses than to gains (Abdellaoui et al., 2008). Several studies have different definition for loss aversion. According to Kahneman and Tversky (1979), in the concept of loss aversion, a prospect of a loss tends to loom larger than that of a gain of the same magnitude, i.e. $u(x) < -u(x)$ for all $x > 0$. This implies that a loss aversion coefficient can be defined as the mean or median of $-\frac{u(-x)}{u(x)}$ over relevant x. Tversky and Kahneman (1992) also, implicitly used $-\frac{u(-1)}{u(1)}$ as an index for loss aversion. In their work, Fishburn and Kochenberger (1979) used a stronger definition of loss aversion that required that $\mathrm{u}'(\mathrm{x}) \leq \mathrm{u}'(-\mathrm{x})$ for all $x > 0$ and indicating that the slope of the utility function at each loss is at least as large as the slope of the utility function at the absolutely commensurate gain. This definition could be related to a loss aversion coefficient of the mean or median of $\frac{u\prime(-x)}{u\prime(x)}$. Other definitions are being proposed by Bowman et al. (1999); Neilson (2002); Schmidt and Zank (2005).

Loss aversion parameters of subjects have been elicited by using lottery games which include negative amount in some choices. In most of these games, subjects typically choose relatively safer options when faced with possible losses than in gains only games (Wik et al., 2004; Yesuf, 2009; Tanaka et al. 2010; Liebenehm and Waibel, 2014). For instance, the results of Yesuf (2009) show that, for the same expected gain, the proportion of subjects preferring the sure income to the gamble doubled when the lower payoff in the gamble changed from a positive amount to a negative amount. The degree of loss aversion has been estimated using the value function where $\mathrm{u}(\mathrm{x}) = x^r$ for all $x > 0$ and $\mathrm{u}(\mathrm{x}) = -\lambda(-x)^r$ for all x < 0. Loss aversion has also been estimated in both developed and developing countries. Tanaka et al. (2010) and Nguyen and Leung, 2010 estimated the average loss aversion of Vietnamese subjects to be 2.63 and 2.05 respectively. These two estimates in developing countries are closer to the 2.25 estimated by Tversky and Kahneman (1992) for US university students. This suggests that the degrees of loss aversion are similar in developing and developed countries. However, the result from Liebenehm and Waibel (2014) indicates that, cattle farmers in West Africa have low loss aversion compared to the results from developing countries in Asia.

This study attempts to measure loss aversion of individuals using a set of ten paired lottery choices similar to Morrison and Oxoby (2014). Several studies attempt to measure loss aversion with hypothetical choices, which has been suggested by several studies to report unreliable proxies for choices affecting real payoffs (see Holt and Laury, 2002). Other studies have also attempted to measure loss aversion by using the difference between the amount individuals are willing to pay for an object versus the amount that they would accept as payment for that object. One major critique of this method is the sensitivity of the object being used, and the interference of the different perspectives of an individual engaged in buying behaviour from one engaged in selling behaviour. The method used in this study is simple has an advantage of eliciting responses to gambles involving monetary losses, rather than hypothetical scenarios.

2.3 Time Preference

The concept of discount rate, which is the rate at which individuals substitute future consumption with current consumption has been used to measure the time preference of individuals. This discount rate is measured by comparing the choice of rewards between two time periods, current or future. Suppose an individual's time preferences over monetary rewards and time pairs is given by (x, t), which is interpreted as x dollars of money obtained at time t, or equivalently, t periods from the time of the experiment (e.g., days, weeks, months, years). Suppose the individuals' preference over monetary payoff is assumed to be linear, then the discount function, $D(x, t)$ is defined so that the individual is indifferent between the pair (x, t) and the pair $(xD(x, t)$,0) (Benhabib et al., 2010). In effect, it is sufficed to say that the value of x at time t is $xD(x, t)$. The discount factor is allowed to depend on the amount of money to be discounted, x, in this case as well as the delay t.

One major concern in the literature of time preferences is the nature and shape of the discount function $D(x, t)$. Classical forms of discounting functions considered in the literature are the exponential discounting function, which is defined as:

$$D(x, t) = exp\{-rt\},\ r > 0 \tag{5}$$

where t is the delayed time at which x is received. Another form discounting is the hyperbolic discounting defined as:

$$D(x, t) = \frac{1}{1-rt},\ r > 0 \tag{6}$$

Both the hyperbolic and exponential discounting are independent of the amount to be discounted, x. However, in contrast to exponential discounting, which is the economically normative model with constant discount rate, preferences that display hyperbolic discounting induce declining subjective interest rates. In particular, while the subjective discount rate, which is defined in general as $|\frac{\frac{\partial}{\partial t}D(x,t)}{D(x,t)}|$, associated with exponential discounting is r, a constant, the subjective interest rate associated with hyperbolic discounting is $\frac{r}{1-rt}$, which is declining in the delay t. It has been observed in most studies (Frederick et al., 2002; Green et al., 1997; Laibson et al., 1997) that, decision makers' behaviour is not consistent with exponential discounting. Another form of a discounting function is the quasi-hyperbolic discounting, which refers to the fact that the valuation of rewards declines more sharply for the future rewards than those in the more distant future (Laibson, 1997; O'Donoghue and Rabin, 1999; Benhabib et al., 2010). This specification expands exponential discounting in a way that it is adequate to reproduce the reversal of preferences (Benhabib et al., 2010).

The basic experimental design for eliciting individual discount rates was introduced Coller and Williams (1999) and expanded by Harrison et al. (2002). This elicitation format takes the form of the multiple price list in the case of eliciting risk preferences which has been criticised to have low level of understanding among rural households by Charness and Viceisza (2016). In this study, I will use a simple task that presents to participants a series of five choices in between two options with a smaller reward delivered an hour after the experiment and a larger reward delivered at a specified time. This task has an advantage of reducing the distrust of participants in paying the future reward since the current reward is paid an hour after the experiment. Also, this task is easy to understand compared with the multiple price list task of Harrison et al. (2002) and thus can induce sensible and meaningful responses.

2.4 Public Good

Public goods are goods that are collectively consumed or produced and are generally defined by two well-known properties of non-excludability, which implies that individuals cannot be excluded from the consumption of the good irrespective of their contribution to its production, and non-rivalry, which also implies that one individual's consumption does not reduce the amount available to others. Individual members of a group have to decide on whether to contribute to the avoidance of a bad or the provision of a good from which all benefits accrue to everyone regardless of whether the individual contributed or not. In effect, some individuals tend to free ride on others contributions by attempting to enjoy the good without contributing.

Even though there is a remarkable diversity of public goods experiments in behavioural economics, a standard one where a group of n individuals (usually between four and ten or even more) are brought together in an experimental lab or together in a field, with each individual given a certain amount of money as endowments (z_i), which he/she has to decide between a part, x_i, that he/she keeps to him/herself, and another part, $c_i = z_i - x_i$, which is invested in the production of the public good has been used. The total contribution, $C =$

$\sum_{i=1}^{n} c_i$, is then used to produce a public good. The individual payoff usually depends on the amount the individuals keeps for his/herself and the total contributions, C, which is usually doubled and shared equally among all the individuals in the group. This experimental task has usually been played repeatedly by same individuals to explore the behaviour of the individuals (Adreoni, 1988; Isaac et al., 1985).

Public good experiments have been used extensively in behavioural economics over the past 25 years and one robust result is that a large majority of individuals voluntarily cooperate even though the Nash equilibrium is to contribute nothing to the public good (Teyssier, 2012; Anderson 2001; Ledyard, 1995). Individuals' behaviour in public good experiments has implications for a wide range of economic situations including producers and consumers' decision regarding the protection of the environment, the choices of both medical practitioners and patients over health insurance, politicians faced with social dilemmas and the policy markers provision of a common good. Individuals contribution in a public good experiment can also serve as a form of insurance for the individuals.

More recent studies have indicated that there is a correlation between individuals' risk preferences and their contributions in a public good experiment. In particular, it has been shown that risk aversion reduces individuals' contributions in public good experiments (Heinemann et al., 2009; Schechter, 2007; Bohnet and Zeckhauser, 2004). Other studies have also indicated that subjects who invested more in a risky asset contributed less to a public good (Charness and Villeval, 2009; Sabater-Grande and Georgantzis, 2002). However, in these studies, the risk preferences of respondents were elicited as well as their contributions in a public good experiment and correlations were drawn, which may result in spurious results. In this study, I test how different degree of exposure to risk impact on the individuals' contributions in a public good experiment. This study, thus, contributes to the literature by investigating how different degree of exposure to risk of natural shocks affects cooperation of rural farmers in a field experiment that is fully incentivised.

3. Design of the Experiment

Experimental design is the process of planning a study to meet specified objectives. Planning an experiment properly is very important in order to ensure that the right type of data and a sufficient sample size and power are available to answer the research questions of interest as clearly and efficiently as possible. In this study, our main goal in designing the experiment was to find different groups that are similar in all domains except for their exposure to risk. In effect, the productivity of crops by districts for the whole country was analysed. In particular, the productivity of eleven crops produced in the country were considered. To be able to compare the productivity of crops produced in each district, the value of productivity, which is measured by the product price and crop yield was computed. The first idea was to pick up two or more districts in different agro-ecological zones with similar mean value of productivity but differ in terms of the variation in the value of productivity.

The East Nzema district, which is in the southern part of the country and lie in the deciduous forest agro-ecological zone and the Tolon-Kumbungu district, which is in the northern part of the country and lies in the Guinea savanna agro-ecological zone were ideal for the experiment (see Appendix A). However, a careful study of the two districts in terms of culture and other socioeconomic characteristics showed that, there are confounding factors in the two districts. For instance, while over 90% of the population in the East Nzema district are Christians, over 90% of the population in the Tolon-Kumbungu district are Muslims. Also, the population in the East Nzema district follow a matrilineal system of inheritance, while the population in the Tolon-Kumbungu district follows a patrilineal system of inheritance.

We, therefore, decided to focus on the northern part of the country, which is more rural than the south and where people rely heavily on agriculture for their survival. Moreover, precipitation patterns in this part of the country are not easily predicted with years of drought being followed closely by years of flooding, with flood being very destructive to crops leaving households in the wake of famine. In 1999 and then again in 2007, the northern region of country was devastated by flooding. For example, the flooding in the year 2007 was preceded by months of drought with the growing months of June and July being dry so that when the rain finally arrived in August, it resulted in, ephemeral streams instead of percolation into the soil[3]. This delay in rain and the heavy onset of rain washed away healthy crops and also caused a loss to those who planted too early. Initial assessment of the losses estimated by the Ministry of Food and Agriculture indicates that about 70500 hectares of farmlands were affected[4], resulting in an estimated loss of 144000 metric tonnes of food crops, which includes maize, rice, millet, sorghum, yam, cassava and groundnuts. Additionally, the floods caused severe damage including the loss of livestock, the destruction of farmlands, houses, bridges, schools

[3] https://www.crwr.utexas.edu/gis/gishydro08/Introduction/TermProjects/Alfredo.htm
[4] http://www.fao.org/fileadmin/templates/tc/tce/pdf/Flash_Ghana_2007.pdf

and health facilities as well as damage to the water supply, food storage and processing facilities, irrigation systems and loss of lives of 20 people (Armah *et al.*, 2011).

There has also being an increase in the occurrence of flood in the northern part of the country in recent times. In 2012, floods destroyed a total of 1725 farmlands in the northern region alone while temporary displacing about 3152 persons in the region[5]. In all, approximately 22008 people were affected by the flood resulting in the death of 3 persons. Floods in 2015 also resulted in the death of 3 people. These examples show how extreme precipitation has have devastating impacts on the livelihoods of households in the northern part of the country. The Tolon-Kumbungu district has been chosen for the experiment because according to the National Disaster Management Organisation (NADMO), the district is flood prone zone. Flood has occurred in this area during the months of July to September in 1995, 1997, 2004, 2007, 2008, 2009, 2010 and 2012. The worst flood in recent times occurred in August 2007, which resulted in the loss of 6 human lives, loss of property and temporary rendering more than 1300 households homeless. Again, over 3000 hectares of farmlands were destroyed in this district with many buildings submerged. Further, the floods also caused outbreak of water-borne diseases including diarrhoea, cholera and malaria, particularly among children (Musah and Oloruntoba, 2013).

The idea is to exploit a natural experiment implied by different exposure to risk in terms of flood and the effects these risks have on the behavioural traits of farmers and their decision-making process in adopting adaptation strategies. In effect, communities that are highly prone to flood and are known to suffer high losses are considered as the treated group, while the least susceptible to flood communities are considered as the control group. Out of the 22 flood prone communities identified in the Tolon-Kumbungu districts, 5 communities (Kuli, Sheegbuni, Nawumi Afayili, and Tampia No. 1 and 2) were selected as our treated group. These communities were purposely selected based on their proximity to the river and easy access to the communities. A total of 5 communities (Wantugu, Gummon, Koblimahigu, Tali and Sabiegu), which are least susceptible to flood were also selected as control groups (see Figure 1; blue dots represent treatments and red dots represent control groups).

[5] https://www.modernghana.com/news/419147/floods-kill-three-affect-22008-people-in-northern-upper-e.html

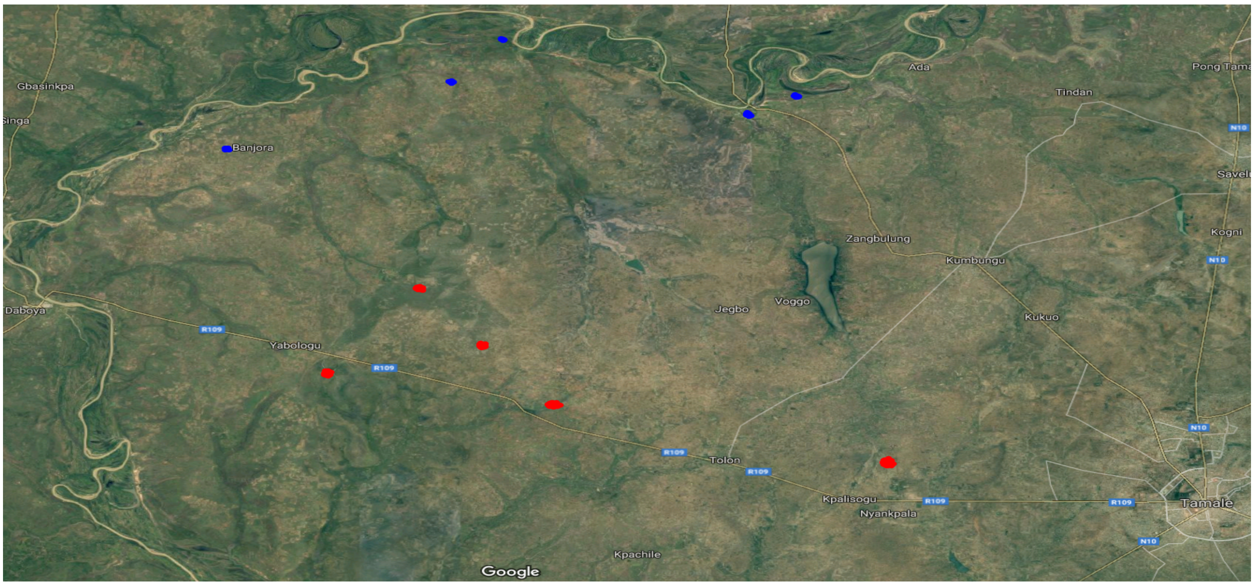

Figure 1: Study Area

3.1 Experimental Design

The experiment consists of four different tasks (risk preferences task, loss aversion task, time preference task and a public good task). A total of 10 experimental sessions were organised in 10 different communities, which consists of 5 treated communities and 5 control communities. A total of 20 participants were used for each experimental session in each location, with each session lasting about three and half hours. In order to reduce heterogeneity and confounds, participants in each community were randomly selected from only male Muslim farmers who predominantly cultivate maize and cassava. Also, to reduce the problems cause by internal mobility of the population, which will lead to the problem associated with self-selection, farmers who have stayed in the communities for more than 20 years were selected for the experiment. In addition, an exit questionnaire was administered in a face-to-face interview format to obtain the socioeconomic characteristics of the respondents and their willingness to invest in their farms. We also elicited farmer's willingness to pay for crop insurance and willingness to access credit. In all, a total of 200 participants were used for the experiment. The experimental tasks used to for the experiments are discussed below.

3.1.1 Risk Preferences

As indicated earlier, the new and improved version of the Bomb Risk Elicitation Task (BRET) which has also been used to elicit risk preferences of 5 year olds was adopted. Participants were asked to imagine to be in a minefield, and on a winding road as shown in Figure 2.

Participants were also made to understand that exactly 1 bomb is hidden behind one of the 100 numbers and that they gain ¢0.50[6] for every step they take. They are to start at step 1, then 2, 3 and so on. Participants are to indicate every step they take by writing a cross over the number, and they are to continue until they reach the step where they want to stop. They also have to write the number of steps that they finally decide to take in the box below Figure 2 on their left.

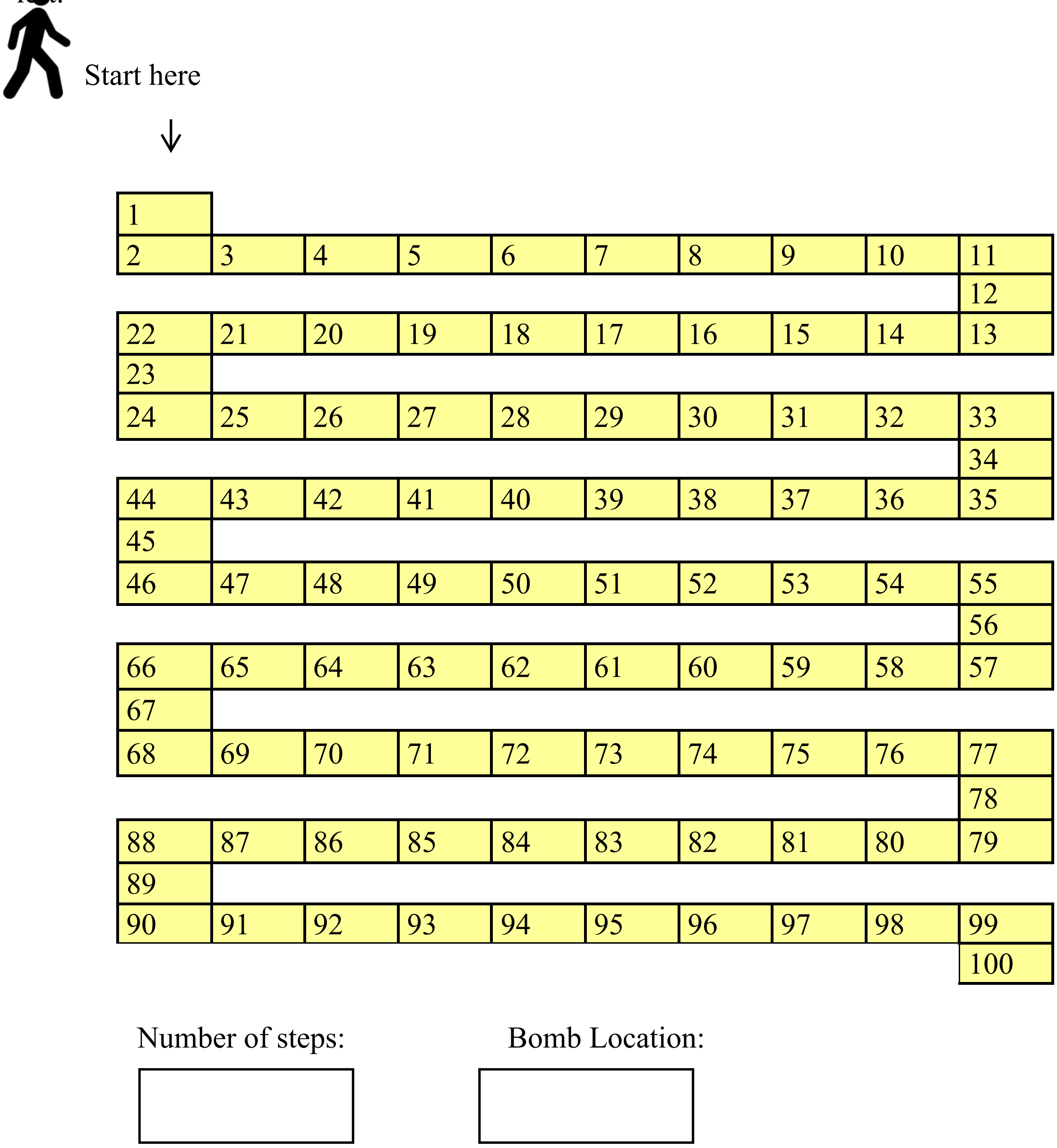

Figure 2: Picture Card for Risk Experiment

[6] Exchange rate the time of the experiment was ¢1= $0.225

The participants were also made to understand that, none of us (the experimenter and the assistants), including the participants knows the bomb's location. However, all of us know that it is equally likely to be behind any of the 100 steps on the winding road. Therefore, they were made to understand that after each participant have decided on the number of steps they will take by writing a cross on each step, the location of the bomb for each participant will be determined by the participant blindly drawing from a bowl containing 100 number and folded papers. The number drawn determined the location of the bomb for that particular participant. If the number drawn from the bowl (which is the bomb location) is greater than the number of steps the participant decided to take, then it implies that the participant did not step on the bomb and earn ¢0.50 for each step he took.

On the other hand, if the number drawn from the bowl is less than or equal to the number of steps the participant took, then that particular participant did step on the bomb and so loses all his money; it means he leaves with nothing. The implication is that, the more steps a participant decides to take on the minefield, the more money he can make, but the risk that he will step on the bomb is also higher. The total number of steps taken would, thus, be used to capture the risk preference of respondents. The lower the number of steps taken in the minefield by an individual, the more risk averse is that individual. In particular, a respondent who take 10 steps in the minefield is more risk averse compared to another individual who takes 15 steps in the minefield.

3.1.2 Loss Aversion

In the loss aversion task, respondents were given a sheet of paper worth ¢10[7] before the start of the task. The task was constructed as a set of 10 decisions between two options, where they have the chance to choose whether they want to keep the ¢10 given to them before the start of the task (option A) or to play a lottery (option B). With option B, respondents always have a 50-50 chance of earning additional ¢10 or lose something and this loss is increasing from row 1 to 10 (see Table 3). The more loss averse individual will switch sooner from option B to option A. In other words, the switching point from B to A is negatively correlated with loss aversion. Monotonic switching was induced in the sense that if a participant chooses option A in the first decision point (first row), then they cannot switch to option B in any of the subsequent decision points.

[7] Exchange rate the time of the experiment was ¢1= $0.225

Also, participants were made to understand that, the moment they switch from option B to option A, they cannot switch back to option B at any point in the subsequent decision points. After the completion of all 10 choices by all the participants, one of the participant was asked to blindly draw one folded paper out of 10 numbered and folded papers in a bowl. The number drawn determined the decision point that all participants will be paid according to the respective choices they made if this task is selected for payment. This task may be influenced by the individuals' risk preferences. In effect, I will test to find out whether individuals responses in this task are influenced by risk preferences by means of a regression.

Table 3: Loss Aversion Task

Decision	OPTION A	OPTION B						
1	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢1**
2	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢2**
3	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢3**
4	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢4**
5	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢5**
6	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢6**
7	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢7**
8	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢8**
9	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢9**
10	**¢10**	**50%**	chance of	**+¢10**	and a	**50%**	chance of	**-¢10**

3.1.3 Time Preferences

The time experiment was constructed as two series of 20 choices each, between two options, which comprises of a smaller reward delivered an hour after the experiment (option A) and larger increasing rewards delivered at a later specified time (Option B). The first series of the experimental task is illustrated by the first 20 decision points and the second series is illustrated by the last 20 decision points in Table 4. In each decision point on the first series, the same amount of ¢5[8] is earned by the participant an hour[9] after the experiment and the delayed reward is changed using a subjective interest rate of a multiple of 365% in each block, which

[8] Exchange rate the time of the experiment was ¢1= $0.225

[9] This is used to reduce the possibility of respondents choosing the current amount because of distrust in the experimenter in paying the future rewards.

corresponds to a particular future time. Therefore, each block in the first series (I, II, III, IV) corresponds to payment in a particular future time period, with the first block representing 24 hours, the second representing one week and so on. It is also worth noting that the interest rate in each block are similar, with the interest rate of 365% in the 1st decision point being the same as the interest rate of the 6th, 11th and the 16th decision points. Also, the interest rate of 730% for the 2nd decision point is the same as the interest rate of the 7th, 12th and 17th decision point.

Choosing option A in each of the decision point in the first series implies that, the participant will rather prefer being given ¢5 an hour after the experiment to a delayed payment of a higher amount of money in a specific time period. A monotonic switching was induced in this task at every block, in the sense that as soon as respondents shift from option A to B in a decision block, they cannot shift back to option A in that block because there is no incentive to do so. Participants' switching point in each block was used to compute his subjective interest rate for that time period. For instance, if in block I, a participant switched from option A to option B on the third decision point, it implies that the participants' subjective interest rate for one day lies between 730% and 1095%. Further, if a participant switched from option A to option B at the fourth decision point in block I, then that participants subjective interest rate for one day lies between 1095% and 1825%. The higher the subjective interest rate, the more impatient the participant. Therefore, by switching from option A to option B, I can test the degree of impatience of the participants, with the more impatient subjects switching later from A to B at each block. In other words, the earlier the individual shifts from option A to option B in each block, the more patient is that individual.

In order to investigate whether presenting respondents with higher amount of current reward changes their discounting for the future compared to lower current amount, a similar task was performed with the current amount being ¢10. Similar interest rates were used to compute the corresponding future rewards in each block, which also corresponds to the future time period. The future time period varies between 24 hours and 3 months, with 3 months corresponding to the maximum amount of time it takes to cultivate maize and harvest. After the completion of all 40 choices by all the participants, one of the participants was asked to blindly draw one folded paper out of 40 numbered and folded papers in a bowl. Respondents decisions at that decision point would be paid for if this game is selected for payment.

Table 4: Time Experiment Task

Block	Decision	Option A	Option B		
I	1	¢5[10] today	¢5.05 in 1 day	A	B
	2	¢5 today	¢5.10 in 1 day	A	B
	3	¢5 today	¢5.15 in 1 day	A	B
	4	¢5 today	¢5.25 in 1 day	A	B
	5	¢5 today	¢5.40 in 1 day	A	B
II	6	¢5 today	¢5.35 in 1 week	A	B
	7	¢5 today	¢5.70 in 1 week	A	B
	8	¢5 today	¢6.05 in 1 week	A	B
	9	¢5 today	¢6.75 in 1 week	A	B
	10	¢5 today	¢7.80 in 1 week	A	B
III	11	¢5 today	¢6.50 in 1 month	A	B
	12	¢5 today	¢8.00 in 1 month	A	B
	13	¢5 today	¢9.50 in 1 month	A	B
	14	¢5 today	¢12.50 in 1 month	A	B
	15	¢5 today	¢17.00 in 1 month	A	B
IV	16	¢5 today	¢9.50 in 3 months	A	B
	17	¢5 today	¢14.00 in 3 months	A	B
	18	¢5 today	¢18.50 in 3 months	A	B
	19	¢5 today	¢27.50 in 3 months	A	B
	20	¢5 today	¢41.00 in 3 months	A	B
V	21	¢10 today	¢10.10 in 1 day	A	B
	22	¢10 today	¢10.20 in 1 day	A	B
	23	¢10 today	¢10.30 in 1 day	A	B
	24	¢10 today	¢10.50 in 1 day	A	B
	25	¢10 today	¢10.80 in 1 day	A	B
VI	26	¢10 today	¢10.70 in 1 week	A	B
	27	¢10 today	¢11.40 in 1 week	A	B
	28	¢10 today	¢12.10 in 1 week	A	B
	29	¢10 today	¢13.50 in 1 week	A	B
	30	¢10 today	¢15.60 in 1 week	A	B
VII	31	¢10 today	¢13.00 in 1 month	A	B
	32	¢10 today	¢16.00 in 1 month	A	B
	33	¢10 today	¢19.00 in 1 month	A	B
	34	¢10 today	¢25.00 in 1 month	A	B
	35	¢10 today	¢34.00 in 1 month	A	B
VIII	36	¢10 today	¢19.00 in 3 months	A	B
	37	¢10 today	¢28.00 in 3 months	A	B
	38	¢10 today	¢37.00 in 3 months	A	B
	39	¢10 today	¢55.00 in 3 months	A	B
	40	¢10 today	¢82.00 in 3 months	A	B

[10] Exchange rate the time of the experiment was ¢1=$0.225

Also, to minimise the possibility of a transaction costs associated with waiting when paid in the future, both current and future payments would be done through mobile money in case this task is selected for payment.

3.1.4 Public Good Experiment

Before the start of the experimental task, participants were grouped together, with each group containing 4 participants. Each member of the group was then given an envelope, which contains a total of 10 toffees, with each toffee worth ¢1[11] to the participant. Each participant then decides individually how many toffees to keep for himself and how many to leave in the envelope (which is his contribution to the group). Participants were made to understand that, the toffees they keep for themselves are for them alone for which they are not going to share with anybody. However, the toffees in the envelope they will put in a box would be doubled and the amount will be shared equally between the four of them regardless of whether someone contributed or not. This game was played 10 times and total contributions were recorded for all the group members to see before the next round of game is performed. I also explained to the participants that after the experiment, one of them will draw a number from 1 to 10 with 1 representing the first round of games and 2 representing the second round of games and so on. What a participant earns on that particular session will be the one I will pay for if that experiment is selected to be paid for among all the 4 experiments.

3.1.5 Procedures and summary of earnings

In addition to all four experimental tasks, an exit survey was administered in a face-to-face interview format to obtain the socioeconomic characteristics of the respondents and their adoption of adaptation strategies. Each participant was paid a participation fee of ¢10 in addition to the real money they won in the course of the experiment, which was on the average ¢21.23 and equivalent to $4.78. The participation fee was set at ¢10 because the current daily minimum wage in Ghana is ¢8.80, which has been increased to ¢9.68 effective from January, 2018[12]. Therefore, in general, participants were paid an average of 3 days' minimum wage. I only paid for one of the 4 experimental tasks which was selected at random at the end of every session by one of the participants in each of the 10 sessions.

[11] Exchange rate the time of the experiment was ¢1=$0.225
[12] http://www.myjoyonline.com/news/2017/july-11th/daily-minimum-wage-goes-up-by-10.php

4. Methodology

To estimate how economic preferences of respondents affect their adoption of adaptation strategies, I first investigated the factors that influences farmers' economic preferences. The classical regression model, which is used to quantify the relationship between response variable (outcome) and predictor variables (covariates) was used to investigate the factors influencing all economic preferences of farmers. This standard regression technique summarises the average relationship between a set of covariates (X) and the outcome variable (Y) based on the conditional mean function $E(Y|X)$. Also, the correlation between farmers' economic preferences and their decisions on willingness to pay for agricultural crop insurance and willingness to contribute to build dams was investigated by means of a standard classical regression model.

However, to investigate the linkage between farmers' economic preferences and their decisions on accessing credit to invest in their farms, I adopted the cumulative distribution function to estimate a regression with the measure of economic preferences of subjects and their socioeconomic characteristics as explanatory variables. This is because, the dependent variable "credit", which is farmers' decisions on whether to access a credit facility is equal to 1 if the farmer decides to access credit and 0 otherwise. This form of dependent variable is known as a limited dependent variable. This form of decision can be modelled by either a logistic function or probit function (Woodridge, 2013). The model for estimating a binary dependent variable is given by:

$$y_i^* = x_i'\beta + \mu_i \tag{7}$$

where y_i^* is unobserved, which is also referred to as a latent variable. From our data, we can assume that a participant chooses to access credit if the utility difference exceeds a certain threshold, which can be set to zero. In effect, we observe $y_i = 1$ if the participant chooses to access credit to invest in his farm, that is, if and only if $y_i^* > 0$, and $y_i = 0$ if otherwise. Consequently, we have

$$P\{y_i = 1\} = P\{y_i^* > 0\} = P\{x_i'\beta + \mu_i > 0\} = P\{-\mu_i \leq x_i'\beta\} = F(x_i'\beta) \tag{8}$$

where F denotes the distribution function of $-\mu_i$ and $-\mu_i$ is assumed to be identically and independently distributed. The subscript i indicates an individual and x_i is a vector of individuals' economic preferences and other socioeconomic factors, which include the participants' household income, age, level of education, treatment, dependency ratio and the size of respondent's farm. Equation (7) can be estimated by maximum likelihood method, with the likelihood contribution of participant i with $y_i = 1$ given by $P\{y_i = 1|x_i\}$ as a function of the unknown parameter vector β, and similarly for $y_i = 0$ (see Verbeek, 2012). Thus, the likelihood function of the entire sample is given by:

$$L = \prod_{i=1}^{N} P\{y_i = 1|x_i; \beta\}^{y_i} P\{y_i = 0|x_i; \beta\}^{1-y_i} \quad (9)$$

or

$$L = \prod_{i=1}^{N} F(x_i'\beta)^{y_i} F(x_i'\beta)^{1-y_i} \quad (9^*)$$

The log-likelihood function can be obtained by taking natural log of equation (9*) to obtain

$$lnL = \sum_{i=1}^{N} y_i ln\, F(x_i'\beta) + \sum_{i=1}^{N}(1 - y_i)\ln\,[1 - F(x_i'\beta)] \quad (10)$$

substituting for the appropriate form of F, that is either logistic distribution or normal distribution, gives an expression that can be maximised with respect to α in order to obtain either a logistic regression or a probit regression estimates.

5. Results

I will first analyse the descriptive statistics of participants' socioeconomic characteristics in order to investigate whether the two groups (control and treated) only differ ex ante as a result of the degree of their exposure to the risk of flood, and also, identify key variables that would be used in the later analysis of economic preferences. I will also present the descriptive analysis of the adaptation measures farmers are willing to adopt in order to reduce the impact of natural shocks on their households and farms. The real choices of farmers in the experimental tasks would also be analysed to investigate whether exposure to risk affects economic preferences. In addition, I will present the multivariate analysis investigating the factors that influences farmers' economic preferences and assessing whether these preferences influence their decision making on adopting adaptation strategies.

5.1.1 Results on the socioeconomic characteristics of groups ex-ante

This section deals with the analysis of socioeconomic characteristics of participants to investigate whether the two groups are the similar ex ante. Results on the ex-ante characteristics of the participants are presented in Table 5. Average household size was found to be 6 with a minimum of 2 household members and a maximum of 11 household members. The results of a Mann-Whitney test show that, there is no significance difference in the average household size of the two samples ($Prob > |z| = 0.244$). There was also no significant difference in the number of adults in each household and dependency ratio, which is measured by the ratio of household members below the age of 15 to household members above the age of 15 ($Prob > |z| = 0.3549$).

The data on education also revealed that majority of the participants (62%) do not have formal education, with the remaining 38% having either a basic or secondary education. Comparing the education level of participants from the two samples, I found out that, while about 66% of the sample in the treated group were illiterates, only 58% of the respondents in the control group were illiterates. However, a Fisher exact test indicates that there is no significant difference in the fraction of respondents who are illiterates in the treated group and the fraction of respondents who are illiterates in the control group ($p = 0.530$). It is also important to note that, of the 38% of the participants who were formally educated in the whole sample, approximately 46% have basic education with the remaining 54% having up to a secondary education qualification.

The average age of respondents was 43.5 years, with the youngest being 27 years and the eldest being 64 years old. There was, also, no significant difference in the age of the respondents in the two samples, even though the respondents in the control group were slightly older than their counterparts in the treatment on the average ($Prob > |z| = 0.303$). I also found out that, there is no significant difference in the number of years respondents have been involved in farming in the two groups ($Prob > |z| = 0.326$), indicating that there are no differences in experience in terms of farming.

On the average, the results show that, farmers cultivate on 4.9 acres of land, which is approximately equal to 2 hectares, with maize and cassava being the major crops grown by these farmers. This confirms the findings by MOFA (2013) and Choudhary et al. (2015), which states that approximately 90 percent of smallholder farmers in Ghana farm on less than two hectares of land and they produce a diversity of crops. The average size of farms in the control group were slightly higher than the average size of farms in the flood prone areas, although the difference is not statistically significant according to a Mann-Whitney test ($Prob > |z| = 0.203$).

Table 5: Socioeconomic characteristics of groups ex-ante

Variable	Control	Treated	Mann-Whitney Z	p-value
Age	44.17	43.05	1.030	0.3032
	(7.58)	(8.59)		
Average Household Income[13]	701.61	694.40	0.710	0.4778
	(93.61)	(99.76)		
Household Size	5.96	6.27	-1.164	0.2443
	(1.71)	(1.84)		
Adult	2.32	2.37	-0.627	0.5307
	(0.57)	(0.60)		
Farming Years	23.52	22.46	0.983	0.3255
	(8.14)	(8.28)		
Farm Size	5.07	4.82	1.273	0.2031
	(1.44)	(1.33)		
Maize Output (100kg bag)	23.25	22.71	1.229	0.2192
	(3.15)	(3.16)		
Cassava Output (100kg bag)	18.45	17.80	1.578	0.1146
	(2.67)	(2.00)		
Price of Maize ($ per bag)	25.67	25.47	0.954	0.3400
	(0.98)	(1.09)		
Price of Cassava ($ per bag)	16.90	16.75	1.636	0.1018
	(0.78)	(0.84)		
Dependency Ratio[14]	2.60	2.66	-0.925	0.3549
	(0.60)	(0.55)		
Education: (Fisher Test)				
No Education	58%	66%		
Basic Education	19%	16%		0.530
Secondary Education	23%	18%		

Source: Author's survey, 2017.

The average maize production by the respondents was about 23 bags, with a minimum production of 17 bags and a maximum of 33 bags. Average maize production in the treated group was less than average production in the control group by approximately 0.5 bags. Statistical test by the Mann-Whitney test ($Prob > |z| = 0.3036$) shows that there was no significance difference in the maize output of the two groups. The results on cassava production also show that the average production in the control group is greater than the average cassava

[13] Household annual average income is the sum of respondents' income from crops, off farm income, remittances and income of other household members working. The amount is in USD

[14] Dependency ratio is the ratio of total household members to number of household members actively working

output in the treated group. However, just like the result on the production of maize, this difference in output was also not statistically significant by the Mann-Whitney test ($Prob > |z| = 0.115$).

The results also show that, on the average households sold about 67% of their maize production (15.48 bags) on the market at an average price of $25.57 per 100kg bag during the previous growing season. On the production of cassava, households produced about 18.13 bags on the average and sold approximately 13.2 bags (73%) at an average price of $16.74 per bag. There was no significant difference in the average price of both maize and cassava that the two groups sold their output, even though the average price is higher for both maize and cassava in the control group (see Table 3).

Annual average total income of respondents' households ranges from a minimum of $517.95 to a maximum of $1057.5. On the average, households earn about $698 per annum, with households in the control group having higher annual income compared to households in the treated group ($701.61 vs $694.4). However, statistical test results show that, there are no significance difference in the mean income of households from these two groups. This is confirmed by a Mann-Whitney test, which also indicates that there is no significant difference in the average income of respondents from the two groups ($Prob > |z| = 0.478$). Also, a Mann-Whitney test on the income from crops shows that there is no statistical difference between the two groups ($Prob > |z| = 0.102$). The results also show that all respondents have spent all their lifetime in the communities I ran the experiment, indicating that there was no migration between the two groups.

5.1.2 Results on the outcome of respondents' exposure to risk

In this section, I analyse the outcome of the treated and control groups in terms of their exposure to risk. The results on the impact of the exposure to the risk of flood on crop production indicate that, farmers in the treated group suffered higher losses compared to farmers in the control group in the previous growing season (see Table 6). For example, in the production of maize, farmers in the treated group lost more than double amount lost in the control group on the average. In particular, whereas farmers in the treated group lost about 5.19 bags of maize in the previous growing season on the average, farmers in the control group lost only about 2.39 bags of maize as a result of their exposure to flood risk. A Mann-Whitney test showed that there is a statistically significant difference in the amount of maize lost in the previous season by farmers in the treated group and the control group, with the treated group losing more maize ($Prob > |z| = 0.000$).

The results also show that there is a very strong statistical significant difference in the amount of cassava production lost in the treated group and the control group in the previous growing period, with the treated group losing more. In particular, the treated group lost about 1.7 bags more of cassava output on the average than their counterparts in the control group ($Prob > |z| = 0.000$). The value of losses was also computed by the amount of crops the farmers lost in the previous growing period and how much they would have earned in the market had they not been lost. This was done by multiplying the losses by the price the respondents sold their output in the market. The value of these losses ranges from a minimum of $68.06 to a maximum of $ 322.88, with an average of about $169.4 in both groups. A Mann-Whitney test indicates that, there was a significant difference in the value of losses reported by the two groups ($Prob > |z| = 0.000$), with the treated group having higher losses as a result of their exposure to flood. In particular, while the treated group lost about $218.44on the average, farmers in the control group were losing only about $120.36 on the average.

Table 6: Analysis of the outcome of the exposure to risk ex-ante

Variable	Control	Treated	Mann-Whitney Z	p-value
Maize Loss (Bags)	2.39	5.19	-12.11	0.000
	(0.88)	(0.87)		
Cassava Loss (Bags)	3.51	5.16	-10.15	0.000
	(0.70)	(1.05)		
Value of Crop Loss ($)	534.93	970.84	-12.07	0.000
	(117.61)	(152.65)		
Loss (Last Year vs Last 5 Years):				
Different	8%	4%		0.373[15]
Similar	92%	96%		

Source: Author's survey, 2017.

It would have been more appropriate to use the average losses over the last five years for the analysis but it was difficult to quantify the losses of the last five with respondents having to recall their exact losses. In order to solve this problem, respondents were asked to indicate whether flood has been occurring frequently over the last five years and whether the losses they reported for the previous year significantly differ from their average losses over the last five years. The results also show that, for about 94% of the respondents, their reported losses

[15] Fisher Exact test p-value

do not differ significantly from their average losses over the last five years. This shows that the losses reported by the respondents are not a one-off occurrence and thus can be used as a good proxy for the impact of the degree of exposure to risk by the different groups.

In all, based on the results of analysis in the two previous sections, I can conclude that our two groups are similar in terms of their socioeconomic and cultural characteristics ex ante. I can also conclude that the two groups differ significantly ex ante as a result of the consequences of their exposure to flood risk. In effect, I have two groups that are only different with respect to their degree of exposure to a natural shock (flood). Therefore, crucially for a field experiment, there is evidence that the design was effective and thus results from the experiment may be trusted.

In order to investigate whether the communities within the treated and the control groups are similar in terms of the value of losses and average income, a Kruskal-Wallis test was performed on each group (see Table 7). The results show that, there are no significant differences in the value of losses within the control group ($|\chi^2| = 2.798;\ p < 0.592$). However, the results from the Kruskal-Wallis test within the treated group revealed that there is significant difference in losses between the villages ($|\chi^2| = 9.747;\ p < 0.045$).

Table 7: Kruskal-Wallis test of equality of populations within groups

Treated				Control			
	Value of Losses				Value of Losses		
Village	Mean	KW χ^2	p-value	Village	Mean	KW χ^2	p-value
1. Tampia 1 & 2	1059.83			6. Wantugu	564.58		
2. Kuli	959.45			7. Gummon	531.33		
3. Afayili	979.18	9.747	0.045	8. Tali	524.55	2.798	0.5922
4. Nawumi	929.95			9. Koblimahigu	549.13		
5. Sheegbuni	925.80			10. Sabiegu	505.08		
	Income				Income		
Village	Mean	KW χ^2	p-value	Village	Mean	KW χ^2	p-value
1. Tampia 1 & 2	2991.38			6. Wantugu	3192.90		
2. Kuli	3248.70			7. Gummon	3107.95		
3. Afayili	2824.60	13.31	0.010	8. Tali	3308.28	9.013	0.061
4. Nawumi	3183.93			9. Koblimahigu	2952.25		
5. Sheegbuni	3182.40			10. Sabiegu	3029.98		

In effect, a Kolmogorov-Smirnov test was also used to investigate the particular communities that cause the difference in losses in the treated group. The results show that the difference in the value losses was caused by the high amount of losses incurred in the Tampia community (see Appendix B). The test on the equality of income with groups shows that there is a significant difference in income within both the treated and the control groups.

5.1.3 Results on adaptation measures

Respondents were also asked to indicate how much they would be willing to sacrifice in monetary terms in order to reduce the impact of climate shocks on their households and farms. In particular, respondents were asked to indicate the maximum amount they will be willing to invest in building a drainage system to reduce the impact of flood on their farms, the maximum amount they would be willing to pay for a bag of fertilizer. In all, a dichotomous contingent valuation method[16] (CVM) with follow up questions, which is used to reduce strategic biases in CVM, was used. Finally, I also asked the respondents whether they would be willing to access formal financial credit to invest in their farms and also whether they would be willing to purchase agricultural insurance. The results on these adaptation measures are presented in Table 8.

Biases might arise at any stage of the CVM design and implementation, which include the construction of the hypothetical scenario (Bishop and Heberlein, 1979), development and application of the method and elicitation procedure for instance starting point bias in bidding games (Boyle et al., 1986; Thayer, 1981). In order to overcome some of the biases involves careful survey and pretesting of questionnaires, competent management of the survey and enumerators, and the use of range of test and observations of the results during the analysis (Wedgewood and Sansom, 2003). For example, one common bias is the starting point biases which arises when the initial bid influences the final willingness to pay (WTP) given by the respondents. In order to minimise this bias, the initial bid should be varied within the sample

[16] The Contingent Valuation method (CVM) is an approach that quantifies the value of an environment or society itself by calculating an amount that measures the WTP of local residents, or the amount of compensation required to agree to changing or eliminating the environment, and by replacing these amounts by pseudo prices. In other words, the CVM approach consists of directly asking individuals the value they attach to environmental resources and its attributes, and to directly state their preferences towards environmental changes. This process estimates the respondents' consumer surplus for the environmental good, and the maximum amount the non-marketed good is worth to the respondent.

frame to examine whether they are influencing the final WTP. In effect, five starting bid prices were used in eliciting respondent's willingness to pay for the hypothetical drainage systems. These bids were set following the results I obtained from the pilot survey.

Respondents were asked to respond either yes or no as to whether they would be willing to pay the initial bid price for the drainage system. The data revealed that only 7% of the respondents said yes to the initial bid price given and gave a higher WTP figure. The rest refused and gave a lower bid than the initial bid price. A spearman test of correlation was used to investigate whether the final willingness to pay values indicated by the respondents was significantly influenced by the initial bid in which case will result in starting point biases. The results show that there was no significant correlation between the initial bid and the final WTP values ($Prob > |z| = 0.200$), indicating that the final willingness to pay to invest in drainage systems were not influenced by the starting bid prices. On the average, each respondent was willing to pay an average of $6.30 per year to build a drainage system to reduce the impact of flood. Results from nonparametric statistical test show that, farmers in the treated group were significantly willing to contribute more for the construction of drainage systems ($Prob > |z| = 0.013$). In particular, farmers in the treated group were willing to pay about $7.02 on the average per year for a drainage system, while farmers in the control were willing to pay about $5.56 on the average per year.

The highest amount that respondents were willing to pay for a 50kg bag of fertilizer, which can help improve crop yield, was also reported by the respondents. Five initial bids, which were set following research about the current subsidised price[17] of fertilizers in the country, were also used to find respondents' true willingness to pay for a 50kg bag of fertilizer. Just like the procedure in eliciting the willingness to pay for a drainage system, respondents were also asked to respond either yes or no as to whether they would be willing to pay the initial bid price for a 50kg bag of fertilizer. Almost all the respondents (94.5%) said no to the initial price and gave a lower bid than the initial price bid, indicating that, respondents perceive the current subsidised price of fertilizer to be very high. On the average, respondents are willing to pay $6.13 per 50kg bag of fertilizer, which is about half the current subsidised price. The results also show that farmers in the control group were significantly willing to pay higher for a bag of fertilizer

[17] http://citifmonline.com/2017/04/07/govt-slashes-fertilizer-prices-by-50/

($6.82) compared to their counterparts in the treated group who were willing to pay $5.31 ($Prob > |z| = 0.000$).

On the respondents' willingness to buy a crop insurance, I asked the respondents to indicate the highest amount they would be willing to pay per annum as insurance premium for their farms. The results show that, respondents were willing to pay an average of $8.95 per annum for insurance. It was also revealed that, farmers in the control group were only willing to pay $8.33 per annum for insurance. Farmers in the treated group, on the other hand, were willing to pay much higher premium ($9.58) for crop insurance. The difference in the amount farmers in the two groups were willing to pay was statistically highly significant by a Mann-Whitney test ($Prob > |z| = 0.002$).

Respondents were also asked about whether they will be willing to buy an agricultural insurance and whether they will be willing to access credit to invest in their farms. While, all the respondents were willing to insure their crops, only 67 respondents, representing about 33.5% of the sample population were willing to access credit to invest in their farms. Of the 66.5% of the respondents who were not willing to access credit to invest in their farms, about 56% were from the treated group, whereas the remaining 44% were from the control group. In addition, non-parametric test shows that, there are significant difference between the two groups in terms of their willing to access credit for farming ($Prob > |z| = 0.011$).

Table 8: Descriptive statistics of adaptation measures

Variable	Control	Treated	Mann-Whitney Z	p-value
WTP for Drainage System per year ($)	5.57 (2.38)	7.03 (3.60)	-2.492	0.013
WTP for Fertilizer per year ($)	6.72 (2.36)	5.31 (1.85)	4.735	0.000
WTP for Insurance per growing season ($)	8.33 (2.77)	9.58 (2.57)	-3.117	0.002
Willingness to Access Credit:				
Yes	42%	25%		0.016[18]
No	58%	75%		

Source: Author's survey, 2017.

[18] Fisher Exact test p-value

5.2 Experimental Results

In this section, I proceed to analyse the actual choices made by the respondents in our experimental tasks in order to investigate whether different degree of exposure to risk have significant effects on the economic preferences of individuals. The results of these actual choices are presented in Table 9.

5.2.1 Risk Preferences

The number of steps the respondents took from the minefield ranges from a minimum of 3 steps to a maximum of 95 steps. On average, the number of steps respondents took was 24.4, indicating a strong degree of risk aversion. This result was not consistent with the study of Vieider and L'Haridon (2016) which indicates that subjects in developing countries are generally less risk averse. This may be as a result of the fact that both groups are significantly exposed to some degree of risk, thereby, making the whole sample in general more risk averse confirming the theory of the relationship between background risk and risk preferences (Cameron and Shah, 2012). On average, subjects from the control group took about 30.5 steps, whereas subjects in the treated took an average of approximately 18.3 steps from the minefield. The result of a Mann-Whitney test indicates that, subjects in the control group significantly took the highest number of steps on the minefield than their colleagues in the treated group ($Prob > |z| = 0.000$). Also, Fisher exact test on the fraction of respondents who are risk averse in both groups shows that there is a significant difference in the fraction of participants who are risk averse in the two groups, with the larger fraction of participants in the treated being more risk averse ($p < 0.012$). In particular, while only about 80% of participants in the control group were risk averse, about 92% of the participants in the treated group were risk averse. This implies that participants in the treated group are significantly more risk averse in general than those in the control group confirming the implication of background risk (Cameron and Shah, 2012).

5.2.2 Loss Aversion

The results on the loss aversion task revealed that a total of 111 respondents representing about 55% of the subjects would prefer the safe option of keeping the $2.25 given to them before the task (option A) in every decision point with the remaining 45% choosing to play the gamble of option B at least once. Out of the 111 respondents who decided to choose the safer option in every decision point, 65 respondents representing 59% were from the treated group, while the remaining 46 respondents were from the control group (see Table 9). Further, statistical test using the Fisher exact test indicates that there is a significant difference in the fraction of participants who decided to choose option A in all decision points in the two groups, with the treated group having the highest percentage ($p < 0.093$). This implies that loss aversion is stronger in the treated group. This result is confirmed by a Mann Whitney test, which was used to test the equality of the average switching point of the two groups ($|z| = 2.906, p < 0.004$). In particular, the results show that there is a significant difference in the average switching point of the two groups, with the treated group having the lowest average switching point, indicating that the treated group are more loss averse compared to the control group.

Table 9: Descriptive statistics of experimental tasks results

Variable	Control	Treated	Mann-Whitney Z	p-value
Risk Aversion (Number of Steps)	30.47 (20.46)	18.26 (18.42)	5.764	0.000
Loss Aversion (Switching Point from B to A):				
Zero[20]	46%	65%		
One	12%	9%		
Two	13%	9%		
Three	7%	8%		0.093[19]
Four	10%	6%		
Five	8%	2%		
Six	4%	1%		
Loss Aversion (Average Switching Point)	1.63 (1.92)	0.91 (1.48)	2.906	0.004
Time Preferences (Subjective Discount Rate, ¢5)	3644.57 (935.8)	3990.13 (781.63)	-3.185	0.001
Time Preferences (Subjective Discount Rate, ¢10)	3243.85 (1180.89)	3729.48 (1057.32)	-3.253	0.001
Public Good[21] (Average Group Contribution)	3.38 (0.36)	4.20 (0.52)	-4.921	0.000

Source: Author's survey, 2017.

In order to investigate whether the responses in the loss aversion task was influenced by respondents' degree of risk aversion, a regression was run on the switching point of respondents with the number of steps (risk aversion) as explanatory variable. Also, the

[19] Fisher Exact test p-value
[20] Zero represents respondents who chose option A in every decision point
[21] Whereas all the other variables have 200 observations, this variable has 50 observations because the respondents were grouped into groups of 4.

treatment group was used as an explanatory variable to investigate whether the degree of exposure has a significant effect of respondents' switching point after controlling for risk aversion. The results from the regression revealed that, there is a statistical significant positive relationship between the switching point and respondents' number of steps taken by the respondents in the risk preference task, indicating that the choices in discussion were influenced by risk aversion (see Table 10).

Table 10: Relationship between loss aversion and risk aversion

Variables	Loss Aversion (Switching Point)
Risk Aversion (Number of Steps)	0.078***
	(0.004)
Treated	0.234*
	(0.123)
Constant	-0.750***
	(0.125)
Observations	200
R-squared	0.796

10000 Bootstrap Standard Errors in parenthesis
***p < 0.01, ** p < 0.05, * p < 0.1

In particular, the results show that respondents who are more risk averse are also more loss averse. Surprisingly, after controlling for risk aversion, there is evidence of loss aversion being weaker in the treated group than in the control group, indicating that different degree of exposure to risk makes people less loss averse. In effect, I can argue that, different degree of exposure to risk does not have a conclusive outcome on respondents' loss aversion.

5.2.3 Time Preferences

In the time preference task, participants were asked to indicate whether they will like to keep the same amount of money at all times or a delayed future reward to be received in a future date. Two series of games comprising of subjective discount rate but different amount for the current payment was used, with the lower current payoff of \$1.13 and a higher current payoff of \$2.25. The goal was to assess whether presenting respondents with higher amount of current reward changes their discounting for the future. A Wilcoxon signed-rank test shows that respondents' subjective average interest rate tends to be much higher when faced with lower current amount (\$1.13) than when faced with higher current amount (\$2.25) ($|z| = 9.31, p < 0.000$). This is consistent with what is found in the literature, which indicate that subjective interest rate is lower for larger amounts (Ikeda, 2016). In effect, the results of the two series, which comprises of low current amount of \$1.13 and high current amount of \$2.25 cannot be collapsed together because there are significant differences in the subjective interest rate for the two rewards in all the future time period, except for one day (see Figure 3).

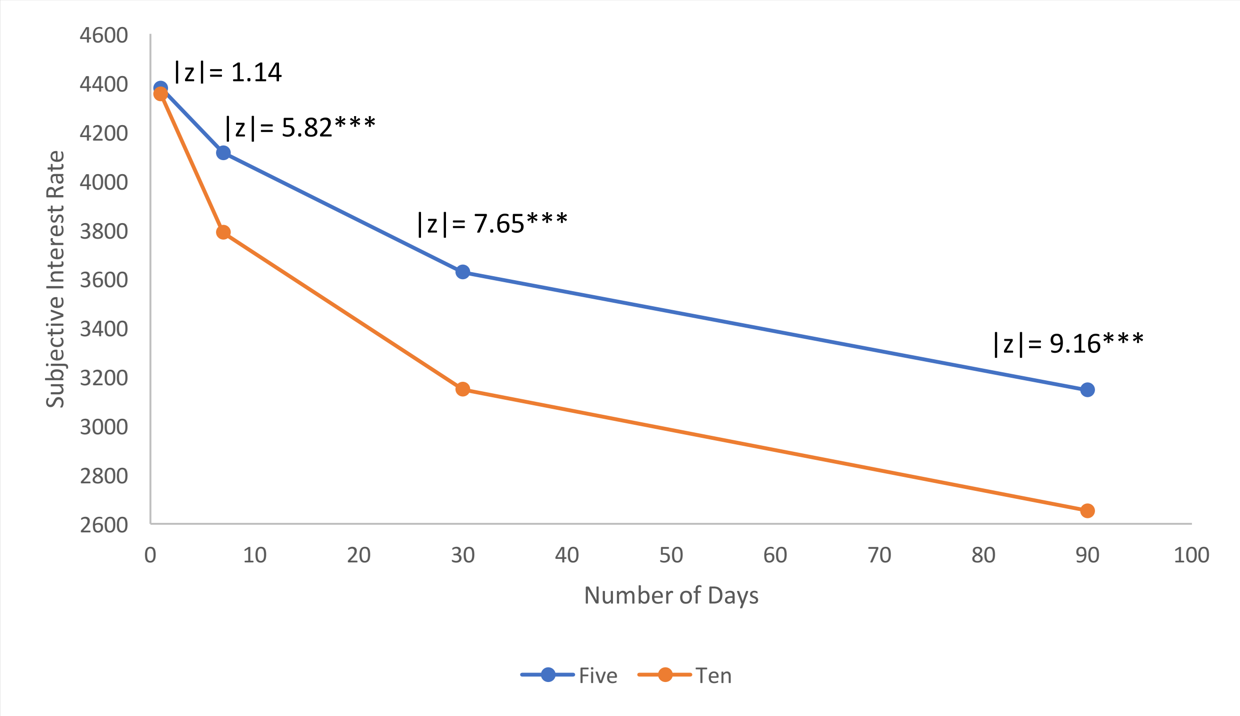

Figure 3: Subjective interest rate of participants with different amount of money.

I, therefore, proceeded to analyse the responses with the lower and higher current rewards separately by the treatment to investigate whether different degree of exposure to risk has significant impact on the subjective interest rate of respondents. A Mann-Whitney test of equality shows that subjective interest rate is significantly higher for the treated group ($|z| = 3.19, p < 0.001$ for lower current reward of \$1.13 and $|z| = 3.25, p < 0.001$ for higher current reward of \$2.25) (see Table 9), indicating that the treated group are more impatient (see Figure 4 a and b). This evidence shows that higher degree of exposure to risk that cannot be avoided makes people more impatient. Similar results were found by Ali Bchr and Willinger (2013), which reported that poor households in villages exposed to volcanic threats in Peru are more impatient. The pattern of the results is also continuous when breaking down by periods.

It is also important to note that the subjective interest rate exhibit a decreasing trend, which is an indication that the subjective interest rate is not constant. This is an evidence against exponential discounting, which states that subjective interest rates are constant over time, but evidence for hyperbolic discounting, which indicates that subjective interest rates are decreasing. This result was further investigated by a means of a regression controlling for treatment effect. The results indicate a strong evidence for hyperbolic discounting, with the treated group having a higher subjective discount rate but less prone to hyperbolic discounting (see Table 11).

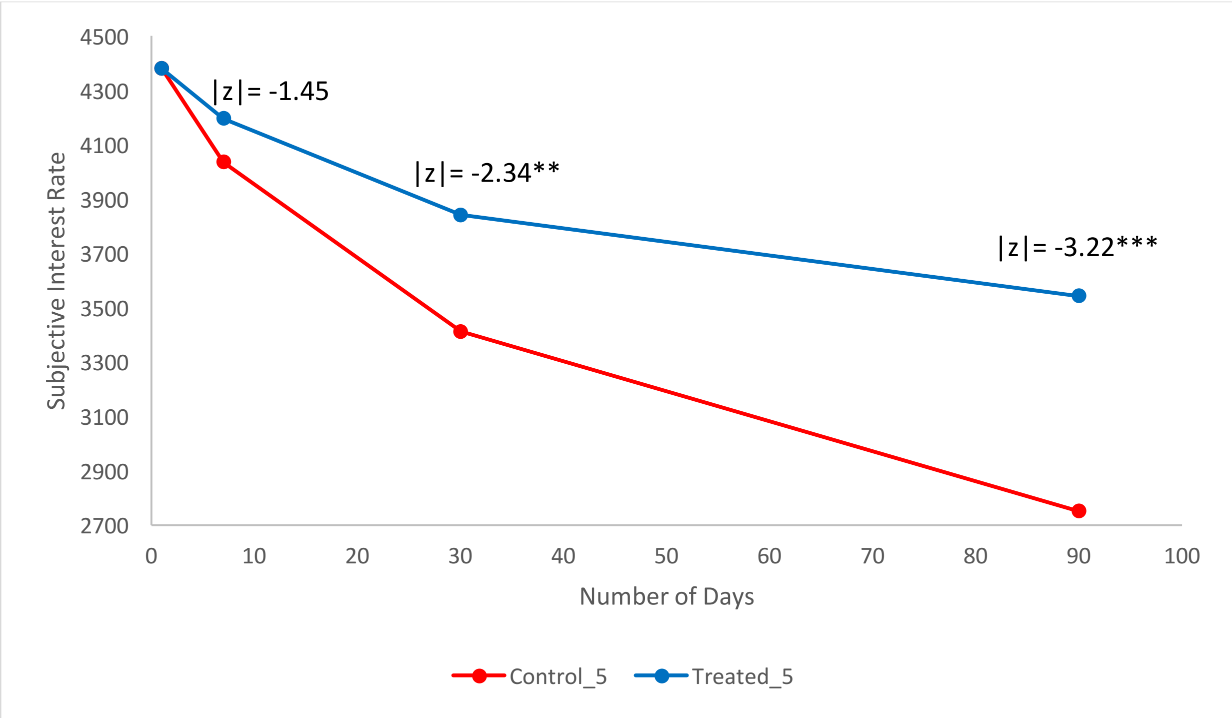

Figure 4a: Subjective interest rate of participants with lower current reward by location

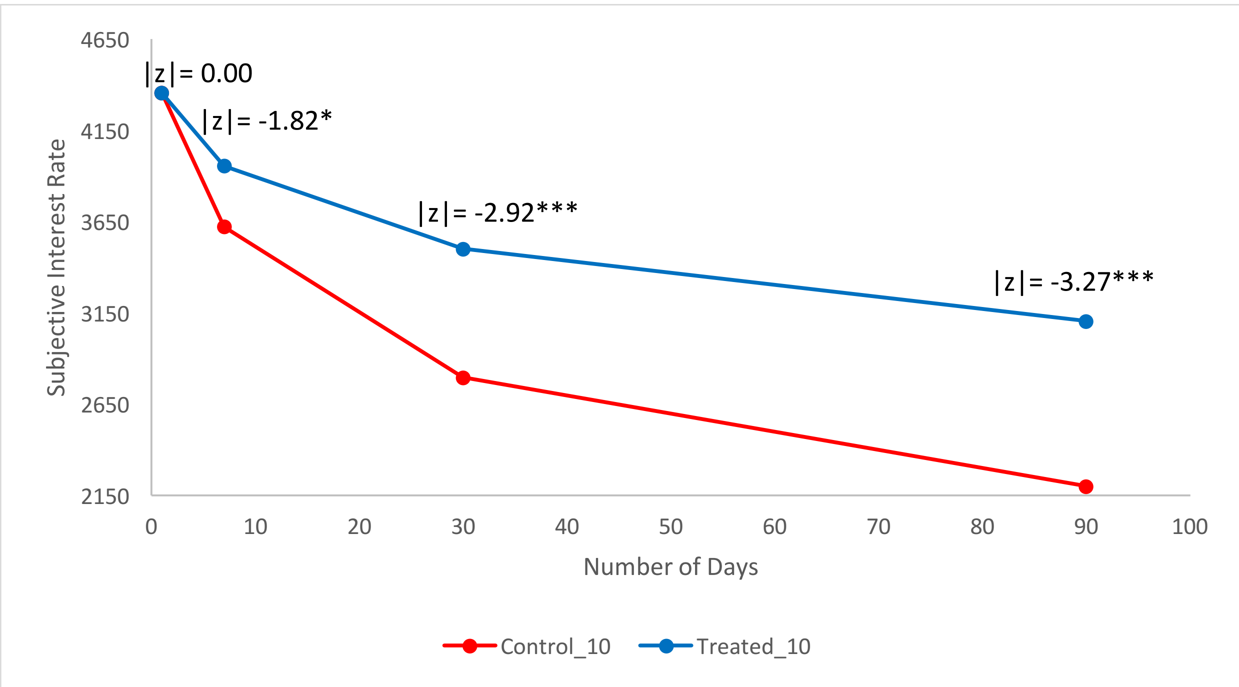

Figure 4b: Subjective interest rate of participants with higher current reward by location

Table 11: Test of Hyperbolic Subjective Interest Rate

Variable	Time (¢5)	Time (¢5)	Time (¢10)	Time (¢10)
Trend	-31.26***	-39.85***	-50.07***	-64.98***
	(4.38)	(6.65)	(5.30)	(7.81)
Trend Square	0.20***	0.24***	0.36***	0.46***
	(0.039)	(0.062)	(0.046)	(0.07)
Trend*Treated		17.17**		29.81***
		(8.74)		(10.16)
Trend sq. * Treated		-0.094		-0.225**
		(0.079)		(0.09)
Observation	800	800	800	800
R-squared	0.265	0.292	0.339	0.363

Robust Standard Errors in parenthesis
***p < 0.01, ** p < 0.05, * p < 0.1

5.2.4 Public Good

The results from the public good task also indicates that, participants are willing to contribute an average of 3.8 out of their total of 10 endowments for a common purpose. On average, the 25 groups in the treated group contributed more per group than the 25 groups in the control group. In particular, while the average contribution in the treated group was 4.2 units, the average group contribution in the control group was 3.4 units (see Table 9). A man Whitney test of the group contributions shows that, the average contributions in the treated group was significantly higher than the average contributions in the control group ($|z| = 5.20, p < 0.000$). This result was also true when I analyse the average contribution by period as shown by Figure 5. The results show that contributions decay after successive rounds of games indicating that free riding was dominant over time (see Figure 5), which is consistent with the results of Isaac et el. (1985) and Andreoni (1988).

As indicated early, previous studies have shown that there is a correlation between risk aversion and cooperation in both positive (Heinemann et al. 2009; Schechter 2007; Bohnet and Zeckhauser 2004) and negative (Charness and Villeval, 2009; Sabater-Grande and Georgantzis, 2002) direction. However, these studies just investigated the relationship between elicited risk aversion of respondents and their contributions in a public good experiment. In this study, I investigated the effects of the different degree of exposure to risk on participants' level of cooperation and the results show that participants who have experienced higher degree of exposure to risk are more cooperative.

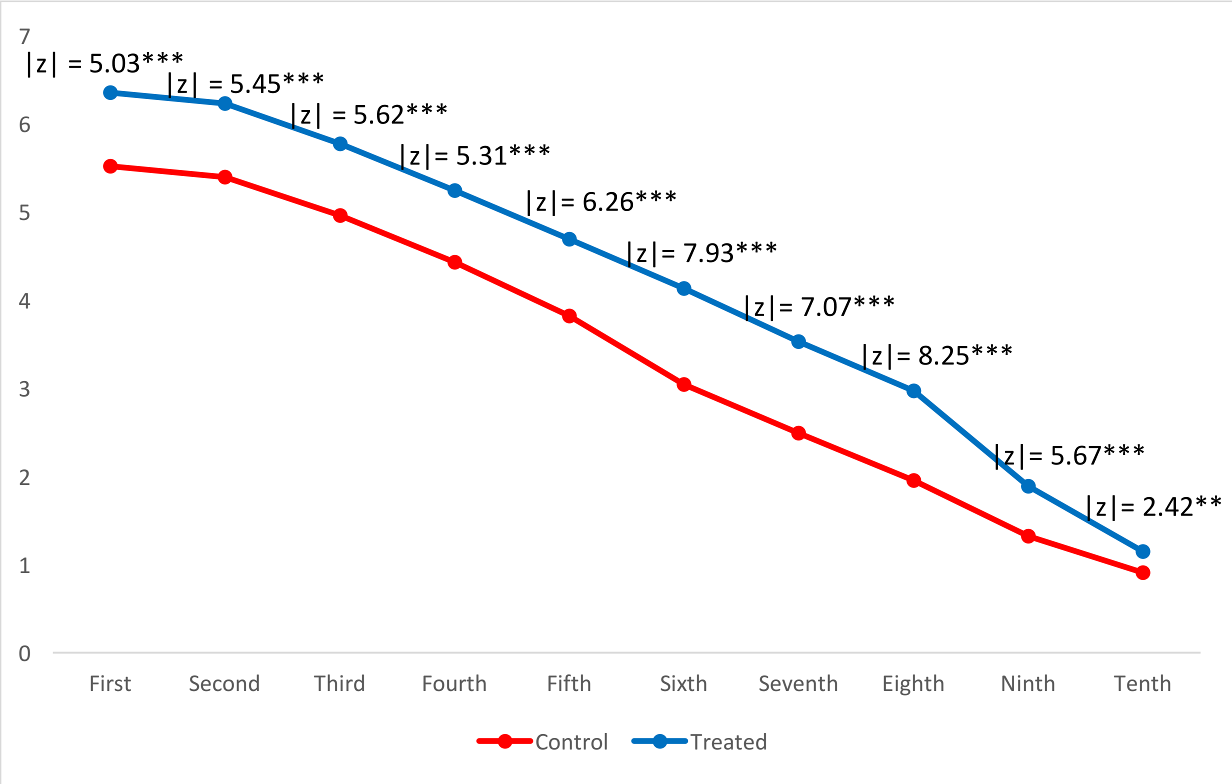

Figure 5: Average group contributions by location.

In order to investigate whether there is a relationship between cooperation and the risk preferences of respondents, a regression was run on the average contributions of respondents with the number of steps (risk aversion) as explanatory variable. Also, the treatment group was used as an explanatory variable to investigate whether the degree of exposure has a significant effect of respondents' average contribution after controlling for risk aversion. The results show that there is a strong positive relationship between cooperation and risk aversion behaviour. This confirms the results of Heinemann et al. 2009; Schechter, 2007; and Bohnet and Zeckhauser, 2004, who reported that risk averse individuals are more cooperative. Also, even after controlling for risk aversion, there was still evidence of cooperation being strong in the treated group than in the control group, indicating that higher degree of exposure to risk makes people more cooperative (see Table 12). Therefore, it is not just risk aversion, exposure to risk makes people more cooperative on top of more risk averse. This implies that respondents perceive cooperation as a form of insurance against the impact of the exposed risk on their households and farms. This is a very import result because, it is the first study that investigates the link between individuals' exposure to risk and cooperation and shows a significant relationship between exposure to risk and cooperation.

Table 12: Relationship between cooperation and risk aversion

Variables	Average Contribution
Risk Aversion (Number of Steps)	-0.011***
	(0.002)
Treated	0.674***
	(0.075)
Constant	3.727***
	(0.070)
Observations	200
R-squared	0.426

10000 Bootstrap Standard Errors in parenthesis
***p < 0.01, ** p < 0.05, * p < 0.1

5.3 Multivariate Analysis

As indicated earlier, in addition to the descriptive analysis, an econometric analysis may provide better information and clearer focus on the factors that influences farmers' preferences and their adaptation measures and also help us to derive policy recommendations. The general approach of this technique was to investigate the relationship between farmers' economic preferences and their socioeconomic characteristics. The treatment was included in the regression to investigate the effect of the different degree of exposure to risk on economic preferences. I also investigated the effects of farmers' economic preferences on the adoption of certain adaptation measures. The variables included in the model were mainly based on the degree of their theoretical importance and their significant impact on economic preferences and adaptation measures.

5.3.1 Factors influencing economic preferences

The correlation between the economic preferences and the socioeconomic characteristics of respondents was estimated by the standard linear regression and the results are shown in Table 9. In order to obtain heteroscedasticity-robust coefficients, the regressions results were obtained from 10000 bootstrapping repetitions. The results on most explanatory variables are as expected and are statistically significant at the 10% significance level or lower. The results of Chi square show that the Wald statistics are highly significant ($p < 0.000$) in all the models, suggesting that the explanatory power of the regression model is very strong. Below I discuss the results on each of the economic preferences considered in this study.

5.3.1.1 Risk Aversion

The results on the relationship between farmers' socioeconomic characteristics and their risk preferences is presented in column (1) of Table 13. The result on the impact of exposure to different degrees of risk on respondents' risk preferences revealed that, respondents tend to be more risk averse when they are exposed to a high degree of risk than when they are exposed to a low degree of risk. This implies that the presence of high degree of risks that cannot be avoided makes individuals more risk averse in general when they have the chance to choose other avoidable risk. This is consistent with the result of Cameron and Shah (2012), who reported that respondents exposed to flood and earthquake in Indonesia exhibit higher levels of risk aversion compared to unexposed respondents.

The results also show that income generally has a negative impact on the risk aversion of respondents. In particular, richer farmers are less risk averse and poor farmers. This implies that, very poor farmers are more risk averse in general, thereby, contributing for them to be trapped in poverty (Liu, 2013; Tanaka et al., 2010). This finding is consistent with many other literatures in developing countries in Asia (Tanaka et al., 2010; Liu, 2013) and Africa (Yesuf and Bluffstone, 2009; Liebenehm and Waibel, 2014). It can be observed that, there is a positive correlation between age and risk aversion, suggesting that the elderly are more risk averse, which is also consistent with similar findings in developing countries (Yesuf and Bluffstone, 2009; Nguyen and Leung 2010; Tanaka et al., 2010; Liebenehm and Waibel, 2014).

On the effect of education on risk aversion, I found out that education, in general, makes people less risk averse. This result is consistent with the findings of Liebenehm and Waibel (2014) among cattle farmers in West Africa, which states that formal education of respondents is negatively correlated risk aversion. The implication of this result is that, education in Ghana makes people more open towards taking up risky opportunities. This may, therefore, help better extension services in the adoption of adaptation strategies, which have an inherent associated risk involved. The impact of education on risk aversion is rather different in Asia, where results of Tanaka et al (2010) and Nguyen (2011) indicate that more years of education may have more positive effects on risk aversion.

Table 13: Factors influencing farmers' economic preferences

Variables	Risk (Steps)[22]	Loss	Impatience	Impatience	Cooperation
Treated	-10.88***	0.258**	381.7***	-39.68	0.690***
	(1.67)	(0.123)	(93.64)	(77.80)	(0.083)
Risk Aversion		0.079***		-38.75***	-0.010***
		(0.005)		(3.467)	(0.003)
Income	0.0211***	-0.0001	-1.089***	-1.213**	-3.3e-05
	(0.0034)	(0.0002)	(0.159)	(0.581)	(0.0002)
Age	-0.517***	0.007	21.82***	1.786	0.007
	(0.112)	(0.008)	(6.94)	(4.808)	(0.006)
Education					
No Edu.	Reference	Reference	Reference	Reference	Reference
Basic Edu.	9.677***	0.001	-716.6***	-342.6***	0.033
	(2.615)	(0.196)	(154.3)	(113.9)	(0.120)
S'dary Edu.	17.35***	0.320*	-1,211***	-538.4***	0.130
	(3.106)	(0.180)	(172.8)	(134.7)	(0.113)
Farm Size	0.951	-0.061	-66.42	-29.57	-0.024
	(0.797)	(0.064)	(41.87)	(40.08)	(0.038)
Depend	2.614*	-0.094	-89.78	11.53	0.044
	(1.532)	(0.116)	(80.47)	(62.21)	(0.073)
Constant	-29.77***	-0.268	6,660***	5506***	3.476***
	(9.901)	(0.696)	(477.8)	(386.4)	(0.464)
R-squared	0.671	0.805	0.666	0.822	0.436

10000 Bootstrap Standard Errors in parenthesis
***p < 0.01, ** p < 0.05, * p < 0.1

5.3.1.2 Loss Aversion

The correlation between respondents' socioeconomic characteristics and loss aversion is shown in column (2) of Table 13. Respondents in the control group were found to be more loss averse than their counterparts in the treated group after controlling for respondents' risk preferences and their socioeconomic characteristics. This implies that respondents who are exposed to high degree of risk that cannot be avoided tends to be less averse to losses when their risk preference behaviours are considered. This is result contradicts the earlier result that the treated group is more loss averse compared to the control group when respondents' risk preference behaviours are not considered (see Section 5.2.2). In effect, it can be argued that the effect of exposure to risk on loss aversion is inconclusive. The results also show that there is a

[22] With respect to the interpretation of the coefficients on risk aversion with number of steps taken, it has to be considered that a negative value of the coefficient implies that the variable has a positive impact on risk aversion and we call it a positive correlation with risk aversion.

positive relationship between risk aversion and loss aversion. In other words, respondents who are highly loss averse are also highly risk averse, indicating that the task maybe influenced by risk aversion.

The results also show that there is a negative correlation between the level of education and loss aversion. In particular, highly educated respondents were found to be less loss averse. There is also a negative correlation between age and loss aversion and a positive correlation between income and loss aversion. However, these results were not statistically significant, indicating that age and income does not influence loss aversion.

5.3.1.3 Impatient Levels

The relationship between farmers' impatient levels, which is measured by respondents' subjective interest rate and their socioeconomic characteristics are presented in column (3) of Table 13. The result show that respondents in the treated group are more impatient than their counterparts in the control group. In particular, the subjective annual interest rate of respondents in the treated group is 381.7% more than the subjective interest rate of respondents in the control group. This implies that the high degree of exposure to risk makes individuals more impatient than the low degree of exposure to risk. In effect, it can be concluded that the presence of risk that cannot be avoided tends to make individuals more impatient (see Section 5.2.3) even after controlling for household socioeconomic characteristics. This confirms the findings of Ali Bchir and Willinger (2013) who consider volcanic threats in Peru and reported that exposure to volcanic threats makes poor households more impatient, but contradicts the findings of Callen (2015).

The results also indicate that there is a negative correlation between income and impatient levels of respondents, which implies that poor people are generally less patient. There is also a positive correlation between education and patience, with better educated respondents being more patient. Just like the results on the relationship between risk aversion and income, these results were also consistent with findings in developing countries in Asia and Africa (Tanaka et al., 2010; Nyugen, 2011; Liebenehm and Waibel, 2014). The age of the respondent was found to have a negative correlation with patient. In particular, the elderly is more impatient, which is consistent with findings in Africa (Liebenehm and Waibel, 2014) and contradicts findings in Asia (Tanaka et al. 2010; Nyugen, 2011). The positive correlation between age and impatient level of respondents in Africa may be as a result of the fact that there is no formal social protection for the elderly in Africa making investment with returns in the far future less attractive to the elderly.

5.3.1.4 Cooperation

The last column of Table 13 shows the relationship between respondents' socioeconomic characteristics and their level of cooperation. The results show that respondents in the treated group were more willing to contribute to for a common purpose, indicating that high degree of exposure to risk that cannot be avoided makes people more cooperative. In particular, respondents in the treated group were significantly willing to 0.8 more of their endowment than their counterparts the control group. Several studies have reported that there is a correlation between risk aversion and cooperation. For instance, according to Charness and Villeval (2009), subjects who invested more in a risky asset contributed less to a public good. Similar result has been reported by Sabater-Grande and Georgantzis (2002), Raub and Snijders (1997). Other studies also did not find significant effect of risk aversion on cooperation (Van Assen and Snijders, 2004; Kocher et al., 2015). The results from this study show that there is a positive relationship between risk aversion and cooperation, indicating that the more risk averse respondents are more cooperative and confirming the findings of Charness and Villeval (2009), Sabater-Grande and Georgantzis (2002) and Raub and Snijders (1997).

However, these studies only elicited the risk preferences of respondents and their contribution for a common purpose and found a correlation between risk aversion and cooperation. In addition, this study exogenously exposed respondents to different degree of risk and the results show that respondents exposed to high degree of risk are more cooperative, implying that the presence of background risk makes respondents more cooperative. This implies that cooperation serves as a form of insurance to respondents who are exposed to risk. This is a very important result because it is the first paper that measures the relationship between the correlation between exposure to risk and cooperation.

There is a negative relationship between respondents' level of income and their level of cooperation. This implies that poorer households are more willing to contribute higher amount for the production of a public good than richer households. The elderly was also found to be more cooperative based on the positive correlation between age and the average contribution of respondents. It was also revealed that the more educated respondents are less cooperative.

however, none of the socioeconomic characteristics are significant in the model controlling for risk aversion.

As earlier stated, a Kruskal-Wallis test showed that, there is a significant difference in the value of losses within the treated group. A further test using Kolmogorov-Smirnov test showed that, the difference in the value of losses within the treated group was caused by the high value of losses in the Tampia community. In effect, as a robustness check, similar analysis was done without the Tampia community and the results do not change significantly. Thus, it can be concluded that the results are robust to exclusion.

5.3.2 Farmers' willingness to access credit and economic preferences

To identify the linkage between farmers' economic preferences and their decisions on whether to access credit to invest in their farms or not, I adopted a logistic regression model. One common problem associated with logistic regression model is the multicollinearity among the independent variables. I, therefore, tested for the presence of multicollinearity in this model by using tolerance and variance inflation factor (VIF). The result of the tolerance and VIF after the logistic regression shows that some of the explanatory variables have VIF above the threshold of 10, indicating that multicollinearity is a serious problem (see column (1) of Appendix C). These variables were thus centred[23] and used for the estimation after testing for multicollinearity (see Appendix C). In addition, jackknife robust standard errors was used to obtain heteroscedasticity-robust coefficients. The regression results from the logistic model of which access to credit is the dependent variable is presented in Table 14.

The signs of the coefficient of most of the explanatory variables are expected. The results of the Wald Chi square also show that the likelihood ratio statistics are highly significant ($p < 0.01$), suggesting that the explanatory power of the regression models are strong. The results show that, being in the treated reduces the likelihood of farmers to access credit in the model without economic preferences. However, this result was only significant in the model without the economic preferences and the model with loss aversion. This implies that, different degree of exposure to risk have a significant effect on willingness to access credit but when the economic preferences are included in the model, the channel through which different degree

[23] I subtracted the mean of the variables from each of the observation to correct for the multicollinearity in the model.

of exposure operates on access credit is mainly through risk aversion, which reduces respondents' probability to access credit to invest in farms.

Table 14: Economic preferences and farmers' willingness to access credit

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treated	-1.388**	-0.383	-1.027	-1.150*	-0.440	0.281
	(0.535)	(0.696)	(0.624)	(0.622)	(0.650)	(0.859)
Cooperation[24]					-1.287***	-0.962
					(0.466)	(0.635)
Loss Aversion[25]				0.949***		
				(0.265)		
Impatient[26]			-0.001***			0.001
			(0.0003)			(0.001)
Risk Aversion[27]		0.108***				0.142***
		(0.032)				(0.050)
Income	0.004***	0.003***	0.003***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.072**	-0.026	-0.046	-0.030	-0.052	-0.023
	(0.034)	(0.042)	(0.039)	(0.044)	(0.036)	(0.048)
Education						
No Education	Reference	Reference	Reference	Reference	Reference	Reference
Basic Education	1.316**	0.307	0.718	1.109*	1.276*	0.506
	(0.577)	(0.670)	(0.627)	(0.600)	(0.686)	(0.772)
S'dary Education	2.171***	0.917	1.112	1.099	2.054***	1.373
	(0.605)	(0.951)	(0.736)	(0.818)	(0.608)	(0.984)
Farm Size	-0.298	-0.345	-0.400	-0.433*	-0.297	-0.272
	(0.238)	(0.242)	(0.249)	(0.261)	(0.247)	(0.241)
Dependency Ratio	0.922**	0.687	0.831*	0.973**	0.829*	0.636
	(0.454)	(0.446)	(0.483)	(0.422)	(0.488)	(0.453)
Constant	-3.426***	-5.326***	0.138	-4.563***	1.161	-5.319
	(1.264)	(1.242)	(1.832)	(1.259)	(1.930)	(3.593)
Observation	200	200	200	200	200	200
Pseudo R^2	0.4152	0.5446	0.464	0.5346	0.4496	0.5642

Jackknife Standard Errors in parenthesis
***p < 0.01, ** p < 0.05, * p < 0.1

[24] Cooperation is represented by the average contribution of respondents over the 10 periods, with higher values representing more cooperation.
[25] Loss aversion is represented by the switching point from B to A, with lower switching point indicating more loss aversion.
[26] Impatient level is represented by the subjective interest rate of respondents, with higher subjective interest rate indicating high impatient levels.
[27] Risk aversion is represented by the number of steps taken, with fewer steps representing more risk aversion.

It is hypothesized that risk-loving individuals will have a higher probability to make risky decisions than risk averse respondents. The estimation results from the logistic regression confirm this hypothesis. This is because, accessing credit to invest in farms, which is deem to be a very high-risk decision, is positively influenced by low risk aversion. In other words, the results show that risk seeking farmers are more likely to access credit to invest in their farms than risk averse farmers. That is, in general, being highly risk averse reduces the probability of the farmer to access credit to invest in their farms. This confirms the findings of Boucher et al. (2008), who reported that, some farmers in Peru are not willing to access formal credit market, even if it would help raise their productivity and income levels because of risk.

The result also shows that there is a positive correlation between patience and respondents willingness to access credit. This implies that more patient respondents are more likely to access credit than impatient individuals. It was also revealed that respondents who are more willing to cooperate are less likely to access credit to invest in their farms. The economic preferences on their own were highly significant after controlling for all the socioeconomic characteristics of the respondents. However, when I combine all the economic preferences, only risk aversion has a significant effect on respondents' willingness to access credit, indicating that risk aversion have a strong significant effect of respondents' willingness to access credit.

Farmers' household income is positively and significantly associated with farmer's willingness to access credit for farming. In effect, it can be anticipated that less risk averse individuals like richer households are more likely to access credit to invest in their farms. This finding is not surprising as it is hypothesised that richer farmers are more willing to take risky decisions. The ratio of household members not working to household members working is also shown to have a significant positive relationship with farmers' decision to access credit, indicating that households with more younger members are more likely to access credit. However, this result is not significant in the full model with all the economic preferences (Model 6).

As expected, the coefficient on farmers' education level is positive in all the models. However, this result was only significant in the models without the economic preferences, model with loss aversion and cooperation. In the literature, an individual's education level has been regarded as a good indicator for his/her ability to understand and use financial tools (Outreville, 2015), which access to financial credit is one of them. The results, therefore, indicates that better educated farmers can better understand the positive implications of accessing credit to invest in farms and thus make them more willing to access credit. In effect, promotional efforts to improve farmers access to credit can focus on the ways in which the positive implications of accessing credit are better explained and communicated to local farmers. Being in the treated group was also found to reduces the likelihood of farmers to access credit. However, this result was only significant in the model without the economic preferences and the model with loss aversion. This implies that, different degree of exposure to risk does not have any significant effect on willingness to access credit when I control for all economic preferences.

5.3.3 Farmers' economic preferences and insurance uptake and willingness to invest in Drainage

In order investigate the relationship between farmers' economic preferences and their decisions on purchasing weather index insurance and willingness to pay for drainage systems, I adopted the standard regression model. Farmers' willingness to pay for insurance and drainage can reasonably expected to be different across groups because they need them more. Nevertheless, it is interesting to analyse the transmission mechanism through which the exposure to risk impacts these adaptation strategies. The dependent variable is the natural log of the amount of money farmers are willing to pay. I adopted the log-transformation of the farmer's willingness to pay as the dependent variable because Schlenker et al. (2006) suggests that a log-transformation outperforms a linear specification, since the distribution is non-negative. The explanatory variables are household's socioeconomic factors, which include farmer's household income, level of education, age, farm size, dependency ratio, location and the economic preference parameters. Two common problems with regression standard linear regression analysis are the presence of multicollinearity and heteroskedastic error terms. As stated earlier, there are two important indices for multicollinearity diagnosis: tolerance and the VIF. The diagnosis results show that the smallest tolerance was greater than 0.17 and the larger VIF was less than 5.75 (see Appendix D), thereby indicating that there is little multicollinearity between these independent variables.

5.3.3.1 Farmers' risk preferences and insurance uptake

The regression results on the relationship between farmers' economic preferences and their decisions on purchasing weather index insurance from the standard linear regression model, with heteroscedasticity-robust coefficient estimates are presented in Table 15. Most of the explanatory variables are expected and the F statistics also shows that the overall the models are all statistically significant ($p < 0.00$), indicating that the explanatory power of the regression models is strong. The results show that respondents in the treated group are more willing to pay higher premiums for agricultural insurance compared to their counterparts in the control group even after controlling for the socioeconomic characteristics of respondents. In particular, this result is statistically significant in all the models, except the model with risk preferences and the model controlling for all economic preferences (Model 2 and 6 of Table 15). This implies that the treatment is effect is still there after individually controlling for each of the economic preferences. However, if I control for all economic preferences, the treatment effect vanishes, with the only significant variable being the risk preferences of respondents, thereby making risk aversion the main transmission of making the treated group willing to pay high insurance premiums.

The estimated results of farmers' willingness to pay for insurance confirm the assertion that risk averse individuals will have a higher probability to take up agricultural insurance than risk seeking individuals (Jin et al., 2016). The coefficient of risk aversion is negative and significant, indicating that risk aversion is positively related to farmer's adoption of agricultural insurance to reduce the impact of climate shocks on their households. This is consistent with standard economic theory and the existing literature on the relationship between individuals' risk preferences and insurance uptake decisions (Simon and Fiorentino, 2014; Jin et al., 2016). There is a positive correlation between impatience and respondents' willingness to pay for insurance.

This implies that less patient respondents are more likely to pay high insurance premiums. In particular, an insurance in the subjective interest rate of respondents by 1 unit increases their willingness to pay as insurance premium by 0.01%. The results also show that there is a positive correlation between loss aversion and willingness to pay for agricultural insurance. Cooperation, however, did not have any significant effect on respondents' willingness to pay for agricultural insurance. It is also worth noting that, even though risk and time preferences are individually statistically significant predictors of respondents' willingness to pay for agricultural insurance after controlling for respondents' socioeconomic characteristics, only their risk preference was statistically significant when all the economic preferences are combined together in one model (see Model 6 in Table 15). This implies that respondents' risk preferences have a strong significant effect on respondents' willingness to pay for agricultural insurance than all the other economic preferences, with risk aversion having a strong positive effect on respondents' willingness to pay for insurance.

Table 15: Economic preferences and farmers' willingness to pay for agricultural insurance

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treated	0.153***	0.031	0.102**	0.099**	0.114**	0.034
	(0.044)	(0.043)	(0.044)	(0.041)	(0.051)	(0.045)
Cooperation					0.049	-0.004
					(0.037)	(0.035)
Loss Aversion				-0.090***		
				(0.018)		
Impatient			0.0001***			-4.8E-06
			(3.2E-05)			(3.8E-05)
Risk Aversion		-0.011***				-0.011***
		(0.002)				(0.002)
Income	-0.0002**	8.2E-05	-9.4E-06	-1.4E-05	-0.0001*	8.1E-05
	(7.5E-05)	(7.7E-05)	(8.0E-05)	(7.8E-05)	(7.5E-05)	(7.8E-05)
Age	0.006**	0.0003	0.003	0.003	0.006*	0.0004
	(0.003)	(0.0025)	(0.003)	(0.003)	(0.003)	(0.003)
Education						
No Education	Reference	Reference	Reference	Reference	Reference	Reference
Basic Education	-0.120**	-0.012	-0.023	-0.052	-0.117**	-0.014
	(0.055)	(0.053)	(0.058)	(0.054)	(0.055)	(0.055)
S'dary Education	-0.173**	0.021	-0.013	-0.021	-0.171**	0.019
	(0.072)	(0.067)	(0.074)	(0.064)	(0.072)	(0.074)
Farm Size	0.004	0.015	0.013	0.006	0.006	0.015
	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)
Dependency Ratio	-0.046	-0.017	-0.034	-0.036	-0.047	-0.016
	(0.045)	(0.040)	(0.043)	(0.041)	(0.045)	(0.040)
Constant	3.921***	3.588***	3.041***	3.685***	3.736***	3.628***
	(0.248)	(0.228)	(0.325)	(0.243)	(0.281)	(0.303)
Observation	200	200	200	200	200	200
Pseudo R^2	0.219	0.374	0.289	0.326	0.225	0.375

Robust Standard Errors in parenthesis
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$

It can be anticipated that more risk averse individuals like poorer households would be more likely to adopt agricultural insurance as natural shock adaptation strategy. This is because, it is hypothesized that, farmers with higher total income tend to be less risk averse and have a smaller demand for insurance (Wang et al., 2016). Wang et al. (2016) also argue that, the decision to buy agricultural insurance is affected by many factors and thus, instead of purchasing insurance, richer farmers could recover through other means such as off-farm investments, if their farms are damaged by bad weather conditions. This hypothesis is confirmed by the results on the impact of household income on risk aversion among farmers in our sample (columns 1 of Table 13) and the result on the impact of household income on uptake of agricultural insurance (model 1 of Table 15). These results show that farmers' household income is negatively related to the amount farmers are willing to pay as agricultural insurance premium in almost all the models except the model with time preferences and the model with all economic preferences. However, the results are only significant in the model without economic preferences and cooperation model. The insignificant results confirm the findings of Wang et al. (2016), whereas the significant results confirm the findings of Jin et al. (2016).

In general, the elderly has been estimated in the literature to be more risk averse compared to the young (Yesuf and Bluffstone, 2009; Nguyen and Leung 2010; Tanaka et al., 2010; Liebenehm and Waibel, 2014) and it is also hypothesized that risk averse individuals will have the higher probability to be covered by an insurance than risk-seeking individuals (Jin et al., 2016). The estimated results indicate that age has a positive significant relationship with the amount farmers are willing to pay for agricultural insurance, thereby confirming this hypothesis.

Even though, the literature suggests that an individuals' level of education is a good indicator for his/her ability to understand and use financial insurance (Enjorlras and Sentis 2011; Ye et al. 2016; Wang et al., 2016), the coefficient of farmer's level of education was found to be negative and significant, indicating that better educated farmers were less incentivized to pay higher amount as insurance premium. This contradicts the findings of Wang et al. (2016) and Jin et al. (2016), whose results show that better educated farmers understand contracts better and thus are more willing to participate in insurance programs. However, I can argue that, better educated farmers are more likely to have other risk management strategies or have the opportunity to engage in a secondary occupation which provides them with additional income, thereby reducing their incentive to pay for crop insurance as a risk management strategy.

5.3.3.2 Farmers' risk preference and willingness to invest in drainage systems

The regression results on the relationship between farmers' economic preferences and their willingness to pay for drainage systems from the standard linear regression model, with heteroscedasticity-robust coefficient estimates are presented in Table 16. The result of the F statistics also shows that the overall the models are all statistically significant ($p < 0.00$), indicating that the explanatory power of the regression models is strong.

The results show that, farmers in the treated group were willing to pay higher for drainage systems than their colleagues in the control group both after controlling individually for the economic preferences and collectively for all the economic preferences, signalling a higher utility of drainage systems for the treated. This implies that high degree of exposure to natural shocks makes individuals more likely to make conscious effort to reduce the negative impacts of the shocks on their households. This confirms the results on the exposure of households to different degree of natural shocks and their willingness to cooperate, which states that high degree of exposure makes individuals more cooperative. The results also show that risk aversion is the main transmission mechanism through which the treated group contribute high for the provision of drainage system, which will help reduce the impact of floods on their farms and households.

The results also show that there is a positive relationship between risk aversion and willingness to pay for investment in drainage systems. This implies that, more risk averse farmers will be willing to invest in reducing the impact of natural shocks on their farms by investing in drainage systems. The results also show that more impatient respondents are willing to pay higher amount for construction of drainage systems that will help reduce the impact of floods on their farms. Also, loss aversion was found to have a positive correlation with respondents' willingness to contribute for the building of drainage system. In addition, the results from the study revealed that, on its own, cooperation has a positive correlation with respondents' willingness to pay for drainage systems, which will help reduce the impact of floods on their farms and households. Surprisingly, if all the economic preferences are analysed together, the result is not significant. This may be as a result of the fact that there is a strong positive relationship between risk aversion and cooperation (see Table 12)

It was also revealed by the results that, there is a significant negative correlation between income and respondents' willingness to pay for drainage systems. This implies that, rather than investing their resources in reducing the impact of natural shocks on their farms and households, rich farmers would rather invest their resources in buying fertilizers, which will improve their yields. In particular, an increase in the income of respondents by one unit will lead to a decrease in the amount respondents are willing to pay for provision of drainage system by 0.03% on the average.

Table 16: Economic preferences and farmers' willingness to pay for drainage systems

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treated	0.411***	0.218***	0.316***	0.326***	0.326***	0.209***
	(0.052)	(0.049)	(0.051)	(0.050)	(0.064)	(0.056)
Cooperation					0.106**	0.016
					(0.048)	(0.041)
Loss Aversion				-0.139***		
				(0.021)		
Impatient			0.0002***			6.1E-05
			(3.4E-05)			(4.2E-05)
Risk Aversion		-0.018***				-0.015***
		(0.002)				(0.003)
Income	-0.0004***	1.5E-05	-8.8E-05	-0.0001	-0.0003***	3.3E-05
	(8.9E-05)	(8.4E-05)	(8.8E-05)	(9.1E-05)	(8.8E-05)	(8.5E-05)
Age	0.011***	0.002	0.006*	0.006**	0.010***	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education						
No Education	Reference	Reference	Reference	Reference	Reference	Reference
Basic Education	-0.156*	0.013	0.019	-0.052	-0.151*	0.033
	(0.082)	(0.059)	(0.070)	(0.064)	(0.079)	(0.059)
S'dary Education	-0.367***	-0.063	-0.070	-0.134*	-0.364***	-0.033
	(0.080)	(0.064)	(0.068)	(0.069)	(0.078)	(0.070)
Farm Size	0.037	0.053***	0.053**	0.039*	0.040*	0.055***
	(0.024)	(0.020)	(0.023)	(0.023)	(0.024)	(0.020)
Dependency Ratio	-0.097*	-0.050	-0.074	-0.080*	-0.098*	-0.051
	(0.051)	(0.041)	(0.048)	(0.044)	(0.051)	(0.041)
Initial Bid	-0.0008	0.0002	0.0003	0.0003	2.7E-05	0.001
	(0.0040)	(0.003)	(0.0036)	(0.0037)	(0.004)	(0.003)
Constant	4.232***	3.650***	2.529***	3.808***	3.788***	3.246***
	(0.395)	(0.334)	(0.434)	(0.379)	(0.457)	(0.460)
Observation	200	200	200	200	200	200
R^2	0.475	0.655	0.588	0.594	0.489	0.66

Robust Standard Errors in parenthesis
***p < 0.01, ** p < 0.05, * p < 0.1

Education was also found to have significant effects on the willingness to pay for drainage systems. In particular, highly educated farmers were found to have lower willingness to pay drainage systems, which would help reduce the risk of flood on respondents' farms, than low educated farmers and farmers with no education who are more risk averse in general. The results show that, being secondary educated decreases farmers willingness to pay for drainage systems by 36% on the average. Also, on the average, being primary educated decreases farmers willing to pay for drainage system by 15%. Dependency ratio was found to have a significant negative effect on the amount farmers were willing to invest on building of drainage systems. This implies that households with fewer family members working were more willing to make investment decisions on reducing the impact of flood on their farms and households. In particular, on the average, an increase in dependency ratio by 1 unit would lead to a reduction in the amount farmers are willing to contribute to build drainage systems by 9%.

6. Summary and Conclusions

Risk and uncertainty play a significant role in almost every important economic decision. For instance, economic preferences among farmers have been identified as important constraints that keep farmers from reaching their productive potential. However, contrary to standard economic hypothesis that indicates that individual's preferences are stable, a growing body of research indicates that there is an endogenous link between individuals living environment and their economic preferences. The effect of the environment on preferences can be linked to background risk, which states that the presence of risks that cannot be avoided or insured against may make individuals less torrent towards other, avoidable risks.

It is also important to note that agriculture plays a dominant role in the livelihoods of households in the sub-Saharan Africa, serving as a stimulus for economic growth, providing food security and assisting in poverty reduction. However, agriculture is susceptible to production and price risk, which impact farmers' income and welfare. Adaptation, which seeks to lower the risks posed by the consequences of natural shocks, is considered the most important policy option in reducing the impact of natural shocks. It involves changes in agricultural management practices in response to changes in conditions. However, most adaptation strategies are also characterized by risk and uncertainty.

In an attempt to investigate how economic preferences reacts to the environment, this study exploited a natural experiment implied by different degree of exposure to risk in terms of flood and the effects these risks have on the behavioural traits of farmers, which is their economic preferences, and their decision-making process in adopting adaptation strategies. In effect, communities that are highly prone to flood and are known to suffer high losses were considered as our treated group, while the least susceptible to flood communities were our control group.

Crucially for a field experiment, there is evidence that the experimental design was effective because the two groups were similar in terms of their socioeconomic and cultural characteristics ex ante but differ with respect to their degree of exposure to a natural shock.

The results show that economic preferences are not stable, with different degree of exposure to risk having significant impact on individual's risk preferences, impatience level and cooperation. In particular, the results show that exposure to risk makes people more risk averse and impatient. The result also revealed that exposure to risk makes people more cooperative. This is a very important result because it is the first study that investigates the link between individuals' exposure to risk and cooperation. There was, however, no strong evidence on the effects of exposure to risk on loss aversion. It was also revealed by the study that the respondents in our sample have a strong degree of risk aversion in general, which is not consistent with the study of Vieider and I'Haridon (2016), which indicates that subjects in developing countries are generally less risk averse. This result may be as a result of the fact that both groups are significantly exposed to some degree of risk, thereby making the whole sample in general more risk averse confirming the theory of the relationship between background risk and risk preferences (Cameron and Shah, 2012). In addition, the result on the effect of different degree of exposure to risk was found to be significant even after controlling for household socioeconomic characteristics indicating that economic preferences are not stable. In all, it was revealed that exposure to risk makes individuals more risk averse, more impatient and more cooperative.

On the factors that influences economic preferences, the results show that income generally has a negative impact on risk aversion, impatience, loss aversion and cooperation. In particular, poor farmers are more risk averse, more impatience, more loss averse and more cooperative. Therefore, improving the income level of farmers would better improve their economic preferences which help them to take make risky investment decisions. Education was also found to have a positive impact on economic preferences, except cooperation, with better educated respondents being less risk averse, more patient and less loss averse. The implication of this result is that; education makes people to be more open towards taking up risky opportunities. In effect, better extension services will help reduce risk aversion, loss aversion and impatient level of farmers in the adoption of coping strategies, which have an inherent associated risk involved. The results also revealed that age has a significant positive correlation with risk aversion and impatience, suggesting that the elderly are more risk averse and impatient. The positive correlation between age and impatient level of respondents may be as a result of the fact that there is no formal social protection for the elderly in Ghana making investment with returns in the far future less attractive to the elderly. In effect, the government should institute policies that will help improve the livelihood of the elderly which will improve their patient levels and also make them take up risky investment. The elderly was also found to be more cooperative based on the positive correlation between age and the average contribution of respondents.

The results on the effect of economic preferences on the adoption of adaptation strategies of respondents revealed that economic preferences individually have significant effects on farmers' willingness to access credit, willingness to pay for agricultural insurance and willingness to pay for the construction of drainage systems to reduce the impact of flood on their farms. In particular, being more risk averse and more impatience reduces the likelihood of respondents to access credit to invest in their farms. More loss averse individuals as well as more cooperative individuals were also less likely to access credit to invest in their farms. Exposure to different degree of risk has a significant effect on all three adaptation strategies, but the main channel through which it impacts respondents' adaptation decisions is through risk aversion. In particular, the results show that being exposed to high degree of risk makes respondents less likely to access credit to invest in their farms, more willing to pay higher agricultural insurance premium and more willing to contribute higher amount for the construction of drainage systems to reduce the impact of flood on their farms and households.

Policy makers should, therefore, focus on improving the risk aversion behaviour of individuals by first reducing the degree of exposure of households to flood, which makes individuals more risk averse. Also, since the level of income was found influence risk aversion negatively, policy makers can influence individuals to make more risky investment by instituting policies that will help improve the income levels of households. The introduction of better extension services, which will help educate farmers on the risk involved in farming and the management practices that will help reduce risk aversion should also be the policy makers' priority.

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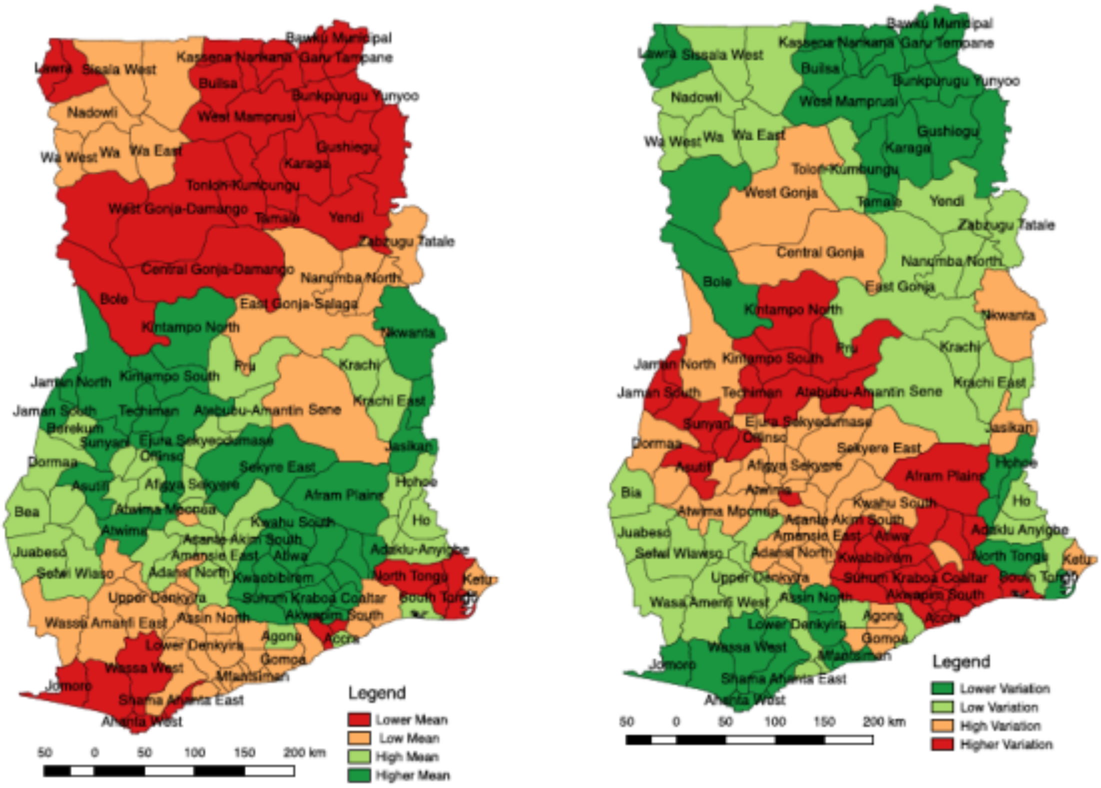
Appendix:



Appendix A: Map showing the distribution of the average yield of all crops by districts.

Appendix B: Kolmogorov-Smirnov test of equality of the value of losses between communities

Treated Group				Control Group			
Community	Mean	KS D	p-value	Community	Mean	KS D	p-value
One Two	1059.83 959.45	0.45**	0.035	Six Seven	564.58 531.33	0.25	0.56
One Three	1059.83 979.18	0.3	0.329	Six Eight	564.58 524.55	0.3	0.329
One Four	1059.83 929.95	0.4*	0.082	Six Nine	564.58 549.13	0.3	0.329
One Five	1059.83 925.80	0.5**	0.013	Six Ten	564.58 505.08	0.3	0.329
Two Three	959.45 979.18	0.2	0.819	Seven Eight	531.33 524.55	0.2	0.819
Two Four	959.45 929.95	0.2	0.819	Seven Nine	531.33 549.13	0.2	0.819
Two Five	959.45 925.80	0.35	0.172	Seven Ten	531.33 505.08	0.2	0.819
Three Four	979.18 929.95	0.2	0.819	Eight Nine	524.55 549.13	0.15	0.978
Three Five	979.18 925.80	0.3	0.329	Eight Ten	524.55 505.08	0.2	0.819
Four Five	929.95 925.80	0.15	0.978	Nine Ten	549.13 505.08	0.3	0.314

***p < 0.01, ** p < 0.05, * p < 0.1

Appendix C: Test of Multicollinearity in Willingness to Access Credit Model suing VIF

Variable	Uncentered	Centred			
		(1)	(2)	(3)	(4)
Cooperation					3.59
Loss Aversion				2.53	
Impatience			2.75		
Risk (Box Selected)	7.05	3.00			
Total Income	70.87	2.28	2.31	2.33	2.22
Age	34.79	1.26	1.38	1.27	1.36
Education					
Basic Education	1.46	1.54	1.28	1.37	1.39
Secondary Education	2.14	2.17	1.45	2.06	1.69
Treated	2.50	1.31	2.22	1.24	2.58
Farm size	25.61	2.08	2.06	2.06	2.06
Dependency Ratio	23.37	1.16	1.15	1.15	1.15
Mean VIF	20.97	1.85	1.82	1.75	2.00

Appendix D: Test of Multicollinearity in the willingness to pay for insurance model using VIF

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Cooperation					1.68	1.8
Loss Aversion				2.1		
Impatience			2.99			5.72
Risk (Box Selected)		3.04				5.75
Total Income	2.2	2.8	2.7	2.5	2.24	2.86
Age	1.34	1.46	1.41	1.39	1.37	1.47
Education						
Basic Education	1.17	1.27	1.34	1.23	1.18	1.35
Secondary Education	1.38	1.74	1.93	1.7	1.38	1.97
Treated	1.03	1.25	1.12	1.1	1.58	1.69
Farm size	2.06	2.08	2.08	2.06	2.07	2.09
Dependency Ratio	1.15	1.16	1.15	1.15	1.15	1.17
Mean VIF	1.48	1.85	1.84	1.65	1.58	2.59

Appendix E: Survey Questionnaire for farmers' exposure to the risk of flood

Date of interview: ____________________ Starting Time: _________________

End Time: ______________________ Interviewee No: ________________

Hello, how are you? Thank you in advance for giving time for this interview. I am Mr. Ebo Botchway. This interview is part of the main body of a research in partial fulfillment of a PhD degree in Economics. Your response to these questions is anonymous and we would treat it with utmost confidentiality. This interview is strictly for academic purposes and therefore honest discussion is the best way ahead. Thank you for your kind co-operation.

I. Demographic Characteristics of the Respondent

1. Gender? 1. Male ☐ 2. Female ☐
2. Age? ___________ Years.
3. Marital status (please tick one):
   1. Single ☐ 2. Married ☐ 3. Separated/Divorced ☐ 4. Other ☐ (e.g. cohabitation without marriage) please Specify _____________
4. Household size ___________ (No. of family members)
5. No. of Adults__________ No. of Children (those less than 15 years) ___________
6. Religion?
   1. Christian ☐ 2. Muslim ☐ 3. Traditional ☐ 4. Other ☐ (specify _______)
7. Level of Education
   1. No Education ☐ 2. Basic ☐ 3. Secondary ☐ 4. Tertiary ☐
8. Years involved in active farming____________
9. What is the total size of your farms in the previous year? ___________acres.
10. Which of these crops did you cultivate last year? (Select as many as possible)
    1. Maize ☐ 2. Sorghum ☐ 3. Rice ☐ 4. Millet ☐ 5. Cassava ☐ 6. Yam ☐
    7. Groundnut ☐ 8. Cowpea ☐ 9. Other______________________
11. On the average, what was your total income from crops for last year?

Crop	Total Yield (Bags)	Bags Sold	Price per Bag (GH¢)	Total Income
Maize				
Sorghum				
Rice				
Millet				
Cassava				
Yam				
Groundnut				
Cowpea				
Other				

12. Do you have other sources of income every year?
    1. Yes ☐ 2. No ☐

If NO skip to Question 13

13. If yes, what are the other sources of income? (Select as many as possible)
    1. Working on someone's farm ☐ 2. Off-farm employment ☐ 3. Remittances ☐
    4. Other ☐ (please specify ___________)
14. How much money do you get from other sources per year?

Source	Amount (GH¢)
Working on someone's farm	
Off-farm employment	
Remittances	
Other	

15. How many people in your family (including yourself) earn their own income ___________ and what is their gross income _________________ either from employment or business or others activities?
16. Are you supporting any person from your disposable monthly income?
    1. Yes ☐ 2. No ☐
17. If **yes**, how much money did you spend per month for this purpose? ______________in Ghana cedis.
18. Are you getting money from anybody in addition to your monthly income?
    1. Yes ☐ 2. No ☐
19. If yes, how much money did you earn per month? ______________GH¢?

II. Migration

20. Have you always lived in this community? 1. Yes ☐ 2. No ☐

If YES skip to Question 27

21. Where did you moved from?
    1. Moved from different part of the district ☐ 2.Moved from different part of the region ☐ 3. Moved from different part of the country ☐ 4. Moved from another country ☐
22. Why did you move to this community?
    1. Because the soil is fertile ☐ 2. Because floods are not frequent here ☐
    3. Because there is a dam for irrigation ☐
    4. Because I have a family here and want to move closer ☐ 5. Other ☐ (specify____)
23. How long have you stayed in this this community? ______ years _____months

24. How has your decision to move improve your farming?
    1. Very useless☐ 2. Useless ☐ 3. No Change☐ 4. Useful☐ 5. Very Useful☐
25. How has your decision to move improve your farm income?
    1. Very useless☐ 2. Useless ☐ 3. No Change☐ 4. Useful☐ 5.Very Useful☐

26. How has your decision to move improve the overall wellbeing of your family?
    1. Very useless☐ 2. Useless ☐ 3. No Change☐ 4. Useful☐ 5.Very Useful☐

III. Respondents' Perception about FLOOD

27. Did you experience any flood during the last year growing season?
    1. Yes ☐ 2. No ☐
28. If yes, on the average, how would you estimate the damage caused by the flood in terms of crops? _______________

Crop	Total Loss (Bags)
Maize	
Sorghum	
Rice	
Millet	
Cassava	
Yam	
Groundnut	
Cowpea	
Other	
Other	

29. Is flood more recurrent in the last 5 years?
    1. Yes ☐ 2. No ☐
30. Do the losses stated in **Question 28** differ from the average losses over the last 5 years?
    1. Yes ☐ 2. No ☐
31. Have you done anything to reduce the impact of flood on your household if it were to occur again?
    1. Yes ☐ 2. No ☐
32. What action have you taken to reduce this impact? (Select as many as appropriate)
    1. Taken credit to invest in farms ☐ 2. Crop insurance ☐
    3. Moved to a least flood prone area. ☐ 4. Use Improved variety of crop ☐
    5. Change planting dates ☐ 6. Building dams for irrigation ☐
    7. Investing in drainage infrastructure ☐ 8. Other ☐ (please specify ___________)
33. Is flood more recurrent in the last 5 years compared to the last 10 years?
    1. Yes ☐ 2. No ☐
34. Have the authorities (eg. Government agencies like MOFA, District Assemblies) made any effort to reduce the risk of flood and drought in the district?
    1. Yes ☐ 2. No ☐
35. What are some of the efforts being made?
    1. Policies to give credit to invest in farms ☐ 2. Promoting Crop insurance ☐ 3. Building dams for irrigation 4. Investing in drainage infrastructure ☐ 5. Other ☐ (please specify________________).

36. Have the members in the community made any effort to reduce the risk of flood and drought in the community?
    1. Yes ☐ 2. No ☐

37. What are some of the efforts being made?
    1.Giving credit to affected households with low interest ☐
    2. Promoting informal crop insurance through ROSCA ☐
    3. Building dams for irrigation ☐ 4. Investing in drainage infrastructure ☐
    5. Other ☐ (please specify_________________).
38. Will you be willing to take loan to invest in your farming?
    1. Yes ☐ 2. No ☐
39. If Yes, how much will you be willing to borrow per growing season? ________GH¢
40. Will you be willing to insure your farm against flood?
    1. Yes ☐ 2. No ☐
41. If yes, how much will you be will to pay per Arce? ______________GH¢
42. Please state the biggest impediments you face when deciding to take some strategies that will help reduce the negative impacts of flood and drought on your crops (Please Rank them)

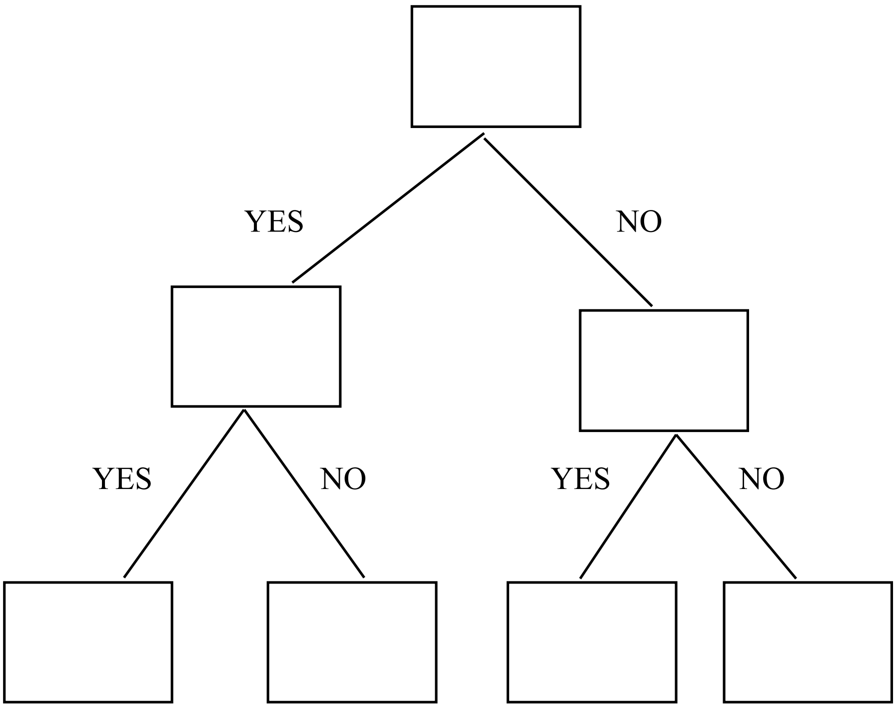
IMPEDIMENT	RANK
Lack of financial resources/credit to purchase farm implements, fertilizers and pay hired labour	
Technological barriers	
Lack of Information on cost and benefits	
Lack of infrastructural development including ready market	
Social-cultural barriers such as belief system and local norms	
Lack of institutional capacity to facilitate agricultural adaptation	
Other	
Other	
Other	

Interviewer: Now read the Hypothetical Scenario to your respondents. Make sure that they pay attention of your description

A. Building drainage system around farmlands

I would like to ask you how much it is worth to you in monetary terms, the provision of a drainage system to combat flooding of farms. The provision of the drainage system among other things means, farmers will have the opportunity to protect their farmlands from flooding when there is excess rainfall during the growing season. It is also important to note that, the drainage system can help the farmer to reduce loss of yield whenever there is excess rainfall by about 90%. However, this drainage system is also expensive and thus need investment. For building the dam for irrigation, assume the district agricultural office is committed in helping farmers to build drainage system. However, before a farmer can have a drainage system around his/her farm, he/she must contribute a yearly fee for the cost of building and for maintaining it. Let us now assume that, you have an option to have this drainage system built around your farm to help reduce the loss of yield from excess rainfall.

A1. Do you think your household would be willing to pay GH¢____for access to the service?



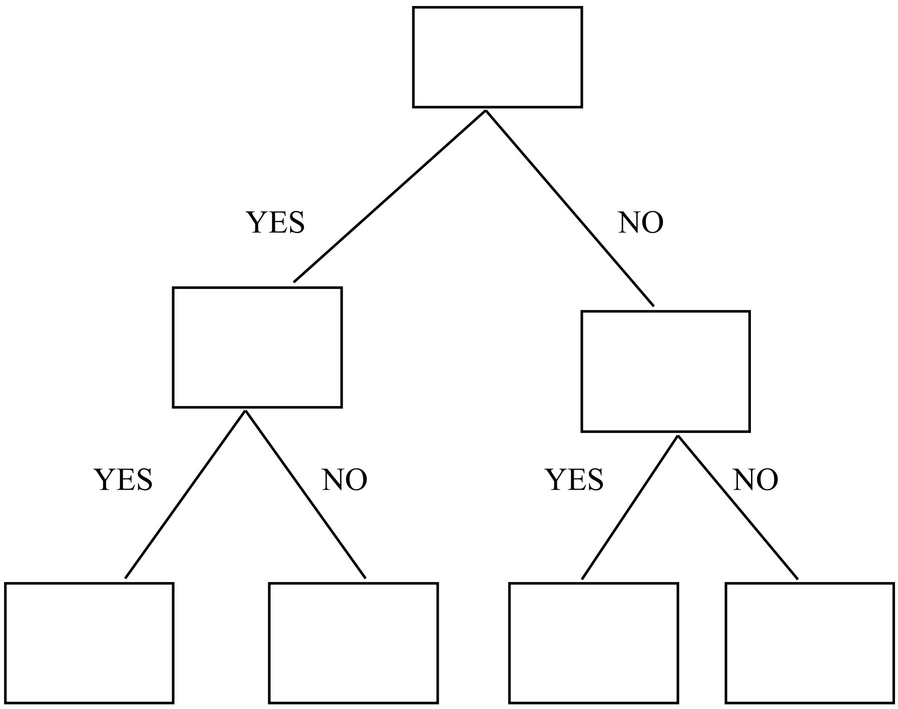
A2. Think for a moment, what is the largest amount of money your household would be willing to pay per year to use this service? If it would cost your household more than this amount, your household could not afford to pay and would not be able to use the service.

Amount of money________________ GH¢ per year

B. Adoption of Fertilizer

I would like to ask you again, how much it is worth to you in monetary terms, the adoption of fertilizers. The adoption of fertilizers mean among other things that, farmers will have the opportunity increase their crop yield by about 50% every growing season. Assume the government is committed in subsiding the cost of fertilizers so that smallholder farmers can afford it. In this case, before you can get a bag of fertilizer to be used on your farm, toy will have to pay the subsidised amount for it.

B1. Do you think your household would be willing to pay GH¢___ for a bag of fertilizer?



B2. Think for a moment, what is the largest amount of money your household would be willing to pay per year to use this service? If it would cost your household more than this amount, your household could not afford to pay and would not be able to use the service.

Amount of money________________ GH¢ per bag of fertilizer.

THANK YOU.

Appendix F: An Experiment to Elicit Risk Preferences of Farmers

In eliciting the risk preferences, I will use the static version of Bomb Risk Elicitation Task. The static version can be played with pen and paper. Because farmers may find it difficult to understand the original version of the task where subjects are face with a 10x10 square of which each cell represents a box, the layout has been change for younger children to understand.

The layout has been changed to represent a road with steps in which a bomb is hidden. In this case, the subject is asked to start from the starting point of the road and walk towards the end of the road. This will be more intuitive to people who do not have higher levels of education.

Instruction for the game: **The Bomb Risk Elicitation Task with pen and paper.**

On the decision sheet of The Bomb Game there is a drawing of a winding road with exactly one hundred steps and they are numbered 1 through 100.

In this approach, subjects are asked to imagine to be on a minefield, which has 100 boxes on the road. A subject gain 1 point for every box he/she pick on the minefield.

In this game, you have to imagine that you are in a minefield, and on the winding road that you see on the paper sheet, exactly 1 bomb is hidden behind one of the 100 numbers. You gain 1 point for every step you take. You have to start at step 1, then 2, 3 and so on. You indicate every step you take by writing a cross over that number (show them how to mark the number), and you continue until you reach the step where you want to stop. You also have to write the number of steps that you finally decide you want to take in the box below on your left. (Please show them the box.*) You do not know the bomb's location. None of us do. You only know that it is equally likely to be behind any of the hundred steps on the winding road. After you have decided on the number of steps to take by writing a cross on each step, I will determine where the bomb is located by rolling two ten-sided dice (00 and 0=100). The die will be shown to the subjects.*

If the number where the bomb is located is higher than the number of steps you have taken, you have not stepped on the bomb and you earn 1 point for each of the steps you have taken. If the number where the bomb is located is lower than or equal to the number of steps you have decided to take, you have stepped on the bomb and lose all your points; it means that you get zero points. So, the more steps you take, the more points you can make, but the risk that you will step on the bomb is also higher.

Example

Try an example to see if they understand the Experiment:

Assuming Kwame takes 25 steps and the bomb is hidden behind number 21.

Will he have stepped on the bomb? ***(Yes or No)***

How many points will he get?

What if Kwame walks 75 steps and the bomb is hidden at step number 79, how many points will he get?

Suppose Kwame walks 48 steps and the bomb also is hidden at number 48, how many points will he get?

Does the number of steps Kwame decides to take have an influence on which step the bomb is located? ***(Yes or No)***

Decision

You now have two minutes to make you decision. I will roll the dice afterwards and I will see where the bomb is located. You can begin now."

Ask subjects "How many steps will you take?"

The participants have two minutes to make their decision, and they also write it numerically below the winding road. The researcher and his assistant will assist and check that this has been done for all the participants, before researcher roll the two ten-sided dice to determine the location of the bomb. The decision sheets are thereafter collected by the experimenters, and the research assistant starts to enter the data in the Excel sheet.

The Bomb Game

Imagine that you are in minefield and 1 bomb is hidden behind one of the 100 numbers below.

You gain **GH¢0.50** for every step you take. If you step on the bomb you lose all your money.

How many steps will you take? Put a cross at every step you take.

The location of the bomb will afterwards be determined by a roll of two ten-sided dice.

Start here

↓

1									
2	3	4	5	6	7	8	9	10	11
									12
22	21	20	19	18	17	16	15	14	13
23									
24	25	26	27	28	29	30	31	32	33
									34
44	43	42	41	40	39	38	37	36	35
45									
46	47	48	49	50	51	52	53	54	55
									56
66	65	64	63	62	61	60	59	58	57
67									
68	69	70	71	72	73	74	75	76	77
									78
88	87	86	85	84	83	82	81	80	79
89									
90	91	92	93	94	95	96	97	98	99
									100

Number of steps:

Points:

Appendix G: An Experiment to Elicit Loss Aversion Behaviour of Farmers

In this game, you will be given a sheet of paper which is worth ¢10. This ¢10 worth of paper will be given to each and every one of you before I start the game. There is this table below, which represents 10 decision points to be taken by you. In each of the 10 decision points, you will be asked to indicate your preference between 2 options, Option A and Option B.

Option A implies that; you will keep the ¢10 given to you before the beginning of this game.

Option B implies that, you will have the chance to either win an additional ¢10, which will be added to the ¢10 I gave you before the start of this game or you will lose some part of or all of the money I gave you before the start of the game by a toss of a coin.

In other words, if you choose option B, I will toss a coin to find out whether you will win additional ¢10 to make you total earnings ¢20 or you will lose some part of the money I gave you before the game.

Before the toss of the coin, I will ask you to choose either a head or a tail. If you choose head and head come up or you choose tail and tail comes up, then, it means that you have won an additional ¢10, which will be added to the initial ¢10 given to you before the start of the game making your total earning ¢20.

However, if you choose head and tail comes up or you choose tail and head comes up, then you will lose some part of the money I gave you before the start of the game.

How the participants will be paid:

At the end of this game, you will select one out of the 10 decision points. I will pay for the decision you made at the decision point you will select from the box. This is how you will select the number; I will write numbers 1 to 10 on pieces of paper and then fold them and put them in a box. Each of these numbers represent a decision point, with 1 representing decision point 1, 2 representing decision point 2 and so on. I will then ask you to pick one of the folded papers. The decision you made on that number will then be paid to you.

For example, if the paper you selected has the number 2 written on it, then the decision you made at decision point 2 will be paid to you. Therefore, if at decision point 2, you chose option A, then you keep the ¢10 I gave you before the start of the game. However, if at decision point 2, you chose Option B, I will ask you to select either head or tail of a coin. I will then toss the coin, if you selected head and head comes up or you selected tail and tail comes up, you have won an additional ¢10 which will make your total earnings ¢20. However, if you selected head and tail comes up or you selected tail and head comes up, then you will lose ¢2 from the ¢10 I gave you before the start of the game making your total earnings ¢8.

Decision Table

Decision	OPTION A	OPTION B					
1	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢1	A	B
2	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢2	A	B
3	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢3	A	B
4	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢4	A	B
5	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢5	A	B
6	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢6	A	B
7	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢7	A	B
8	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢8	A	B
9	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢9	A	B
10	Keep ¢10	If HH or TT, you win	+¢10	If HT or TH, you lose	¢10	A	B

Appendix H: An Experiment to Elicit Time Preferences of Farmers

In this game, you will be given a sheet of paper that has a table printed on it. This table represents a total of 8 decision points that will be taken by you. You will be asked to indicate your preference between 2 options, **Option A** and **Option B**. Choosing option **A** implies that, you will prefer rather being given an amount of money an hour after the experiment than wait for some specific amount of time to be paid an amount higher than what is paid an hour after the experiment. Choosing option **B**, implies that you will rather wait for some time and receive an amount higher than what will be given to you 1 hour after the experiment.

Note that at every block has 5 decision points, option A has the same amount of money but option B has different amount of money with different interest rate. Each block corresponds to a decision concerning a particular future time period. Block I correspond to future payments in 24 hours-time, Block II corresponds to future payment in 1 week, Block III corresponds to future pay in 1 month and Block IV corresponds to future payment in 3 months-time.

So, in each block you have to make 5 decisions comparing the amounts payable in option A and option B. You can switch from option A to option B, but you cannot switch from option B to option. Thus, if you choose option B in the first decision point in block A, you cannot switch to option A at any point in that block. This is because if you prefer being paid ¢5.05 in 1 day to being paid ¢5 an hour after the experiment (Decision point 1), then you will definitely prefer being paid ¢5.10 in a day to being paid ¢5 an hour after the experiment.

Example

1. At decision point 1 of Block I, if you choose option A, then you are saying that you will rather be willing to receive ¢5 an hour after the experiment than wait 24 hours to be paid ¢5.05. If decision point is selected for payment, then I will pay you ¢5 by mobile money an hour after the experiment. However, if you choose option B at decision point one in Block I and that point is selected for payment, then I will wait for 24 hours and then pay you via mobile money an amount of ¢5.05.

Note:

1. You will have to make a choice between option A and B in all the 40 decision points.
2. You are also to note that once you switch from option A to B in each of the 8 blocks, there is no incentive to switch back to option A. Therefore, if you choose option B in the first decision point in each of the 8 blocks (decision points 1, 6, 11, 16, 21, 26, 31 and 36), you cannot switch to A at any point in that block.

Below is the Decision Table.

Decision Table

Block	Decision	Option A	Option B		
	1	¢5 today	¢5.05 in 1 day	A	B
	2	¢5 today	¢5.10 in 1 day	A	B
I	3	¢5 today	¢5.15 in 1 day	A	B
	4	¢5 today	¢5.25 in 1 day	A	B
	5	¢5 today	¢5.40 in 1 day	A	B
	6	¢5 today	¢5.35 in 1 week	A	B
	7	¢5 today	¢5.70 in 1 week	A	B
II	8	¢5 today	¢6.05 in 1 week	A	B
	9	¢5 today	¢6.75 in 1 week	A	B
	10	¢5 today	¢7.80 in 1 week	A	B
	11	¢5 today	¢6.50 in 1 month	A	B
	12	¢5 today	¢8.00 in 1 month	A	B
III	13	¢5 today	¢9.50 in 1 month	A	B
	14	¢5 today	¢12.50 in 1 month	A	B
	15	¢5 today	¢17.00 in 1 month	A	B
	16	¢5 today	¢9.50 in 3 months	A	B
	17	¢5 today	¢14.00 in 3 months	A	B
IV	18	¢5 today	¢18.50 in 3 months	A	B
	19	¢5 today	¢27.50 in 3 months	A	B
	20	¢5 today	¢41.00 in 3 months	A	B
	21	¢10 today	¢10.10 in 1 day	A	B
	22	¢10 today	¢10.20 in 1 day	A	B
V	23	¢10 today	¢10.30 in 1 day	A	B
	24	¢10 today	¢10.50 in 1 day	A	B
	25	¢10 today	¢10.80 in 1 day	A	B
	26	¢10 today	¢10.70 in 1 week	A	B
	27	¢10 today	¢11.40 in 1 week	A	B
VI	28	¢10 today	¢12.10 in 1 week	A	B
	29	¢10 today	¢13.50 in 1 week	A	B
	30	¢10 today	¢15.60 in 1 week	A	B
	31	¢10 today	¢13.00 in 1 month	A	B
	32	¢10 today	¢16.00 in 1 month	A	B
VII	33	¢10 today	¢19.00 in 1 month	A	B
	34	¢10 today	¢25.00 in 1 month	A	B
	35	¢10 today	¢34.00 in 1 month	A	B
	36	¢10 today	¢19.00 in 3 months	A	B
	37	¢10 today	¢28.00 in 3 months	A	B
VIII	38	¢10 today	¢37.00 in 3 months	A	B
	39	¢10 today	¢55.00 in 3 months	A	B
	40	¢10 today	¢82.00 in 3 months	A	B

How the participants will be paid:

At the end of this game, one you would be asked to blindly draw one folded paper out of 40 numbered and folded papers in a bowl. Each participants' decision at that decision point would be paid for if this game is selected for payment. One of you will select one out of the 40 decision points. This is how you will select the number; I will write numbers 1 to 40 on pieces of paper and then fold them and put them in a bowl. Each of these numbers represent a decision point, with 1 representing decision point 1, 2 representing decision point 2 and so on. I will then ask you to pick one of the folded papers. The decision you made on that number will then be paid to you. For instance, if the participant pick the number 36 from the box, then I will look at the decision you made at decision point 36 and pay you accordingly.

Appendix I: Public Good Experiment

Before the start of this experiment, I will give you an envelope, which contains a total of 10 toffees. Each toffee in the envelope is worth **¢1** of real money to you. I will then group all of you into a group of 4 members in each group. Each participant will then decide individually how many toffees to keep for himself and how many to leave in the envelope (which is his contribution to the group). Remember each toffee is worth **¢1** so if you keep all 10 toffees you have **¢10** for yourself, if you keep 5 toffees, you have **¢5**, if you keep 2 toffees, you have **¢1** for yourself and so on.

Do not let anyone see the amount you took for yourself and also do not tell anyone about it. You are also not allowed to discuss anything with anybody. In other words, nobody in the group will have to know how many toffees you took out for yourself and how many toffees are left in the envelope.

The number of toffees in the envelopes, which represents the total contributions by all the 4 members in the group would be doubled and shared equally among the group members, regardless of the amount each participant contributed. In effect, the **payoff** each and every one of you get will be the **amount of money you kept for yourself** plus the **doubled sum of money in the box divided by 4**, which is the number of individuals in the group.

For example, if one of you kept 5 toffees for him/herself and the group in total contributed 24 toffees, then you total payoff will be ¢17 = [(¢5)+{(24*2)/4}]

In order to observe the strategic behavior of the participants, the game will be played 10 times.

At the end of the 10th game, one of you will select one out of the 10 games for which I will pay you. This is how you will select the number; I will write numbers 1 to 10 on pieces of paper and then fold them and put them in a box. I will then ask one of you to pick one of the folded papers, the number he will pick will represent the game that you will be paid. For example, the number 1 represents the first game, 2 represents the 2nd game and 10 represents the 10th game. Therefore, if the number he picked is 5, then it means that all of you will be paid the payoff you earned in the 5th game.