Three essays on economic evaluation of responses to weather-induced risks in Uganda

by

Florence Lwiza

B.S., Makerere University, 2005
M.S., Uganda Martyrs University, 2009

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

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Abstract

In Uganda, the past five decades have been characterized by increasing temperatures, longer dry seasons, changes in the timing of rainfall with extreme events such as floods and heavy rainstorms, all of which have adverse effects on the livelihood of the rural farming community. Several strategies have been recommended for adaptation and mitigation of negative effects arising from changing weather conditions, including migration, use of weather index insurance, and changes in farm production practices, among others. However, the usability and effectiveness of the strategies are influenced by economic, social, biophysical and farmers' behavioral factors that are examined in the three essays of this study.

Given the importance of weather and labor to rural and agricultural-based economies, the first essay examines the effect of weather anomalies on the likelihood that workers migrate from rural and urban areas. By matching household survey data with weather data, and assuming exogeneity of weather variables, the effects are identified by exploiting the spatial heterogeneity of weather conditions and worker characteristics. The results remain robust to alternative model specifications, all of which show a nonlinear effect of weather anomalies on the likelihood of migration of workers from rural areas. The results show that precipitation extremes reduce the likelihood of labor migration whereas temperature extremes increase the likelihood of labor migration. This research contributes to the burgeoning literature on weather-induced migration, and the findings underscore the need to build resilience for workers.

The second essay analyzes the critical temperature for coffee yield reduction and whether the effects for single-cropped coffee farms differ from those that are intercropped

with bananas as shade plants. Using panel data for coffee production and weather, I exploit the spatial and temporal variations in temperature and precipitation to estimate the effects. Estimation of random-effects regression models shows a nonlinear effect of temperature and precipitation on the yield for coffee with extreme temperatures greater than 28^{o}C resulting in yield reductions. A sensitivity analysis predicts that increases in temperature results in reductions in yield, but the reductions are less for coffee farms that are intercropped with bananas. The findings can be used to inform policy decisions and research to design interventions that reduce production risks arising from weather changes.

The third essay analyzes factors that affect adoption and renewal of weather index-based insurance contracts. It also examines farmer preferences for attributes and types of index insurance contracts. Given that the use of index insurance is relatively new in Uganda and the market is not yet well developed, the study makes use of data collected through choice laboratory experiments conducted in simulated insurance markets in Western and Central Uganda. Discrete choice models were used to analyze the data and the results showed that the ambiguity of insurance contracts reduces the likelihood of the adoption of insurance. The results also show that farmers have a higher preference for insurance offered through farmer groups, as opposed to insurance offered to individuals. The study contributes to the literature on behavioral and product-specific factors that affect the adoption of index-based insurance.

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Approved by:

Major Professor
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Dedication

To my parents and my little girls, Jordana, Joana and Johnnette

Chapter 1 - Weather Anomalies and Labor Mobility in Uganda

1.1 Introduction

In many countries of Sub-Saharan Africa, the past two decades have been characterized by increasing temperatures, changes in the timing and intensity of rainfall, and increased occurrences of weather shocks or weather-induced disasters such as floods and landslides (Serdeczny et al. 2017; Niang et al. 2014). The effect of increasing temperatures on agriculture has been examined in many studies and these show that increased temperatures beyond a historical average significantly affect land use, land value, crop choice and crop yield, especially for non-irrigated crops (Bohra-Mishra et al. 2017; Feng, Oppenheimer and Schlenker 2015; Tack, Barkley and Nalley 2015; Lobell et al. 2013; Feng, Krueger and Oppenheimer 2010). However, the effect of changing climate and weather patterns on labor has not been extensively explored.

Labor is an important factor of production in developing countries, where the level of agricultural mechanization is low. However, gradual increases in temperature, precipitation as well as occurrences of weather-induced disasters have adverse effects on employment and earning for workers whose livelihood depends on agriculture, such as farm laborers, traders, and processors for agricultural produce (Marchiori, Maystadt and Schumacher 2012). Extreme weather changes can affect labor productivity, earnings and demand for labor. Weather-induced disasters can also lead to labor displacement, death and significant economic losses that can induce labor migration indirectly through disruption of socio-economic activities and adjustments in prices and wages (Maurel and Kubik 2014).

Uganda is one of the countries that have experienced gradual increases in temperatures over the past four decades, with an estimated increase in temperature by 1^{o}C every decade. It is anticipated that temperatures will increase by up to 1.5^{o}C between 2030 and 2052 (Masson-Delmotte et al. 2018). Because of the adverse effects of extreme weather events and gradual weather changes, the agricultural sector in Uganda is characterized by increasing rates of occupational and geographic labor mobility. Occupational mobility is observed when workers move from an agricultural job to a non-agricultural job, whereas geographical mobility is observed when workers move to a different location that could be a rural area, urban area or foreign country. In most cases, occupational mobility leads to geographic mobility. Migration to locations and occupations that are less susceptible to extreme weather changes remains one of the strategies that workers can employ to guard against employment uncertainties, income and consumption fluctuations resulting from weather changes. However, it is not clear whether migration is an option for workers from low wealth households. This is because migration involves upfront travel and relocation costs that are more affordable by workers from wealth households. Workers who migrate also incur nonfinancial costs such as loss of social networks (Borjas 1989).

The burgeoning literature on weather-induced migration focuses mainly on the effect of climate change on cross-border migration or international migration. While such literature is important in identifying possible relations between human mobility and changes in climate, it shows macroeconomic effects based on long-term country averages of weather variables that do not capture spatial variations in precipitation and temperature exposure. Studies such as Grace et al. (2018), Bohra-Mishra et al. (2017) and Henry, Schoumaker and Beauchemin (2004) examined internal or within-country migration and these focused more on the movement of workers from rural to urban areas, with less emphasis on intra-rural migration that is more prevalent. There is, therefore, a growing interest to understand the factors influencing redistribution of populations within rural and urban areas. This study examines the effect of temperature extremes, precipitation changes and extreme weather events such as floods and landslides on the likelihood that a worker migrates from a rural or urban area within Uganda. This research contributes to the existing literature by empirically examining the effect of gradual changes in weather patterns and weather shocks on workers' decisions to migrate using location-specific weather variables. The study focuses on internal, or within-country migration, because migration costs as well as legal barriers constrain most migrants to moving within the borders of the country (Beine and Parsons 2017; Marchiori, Maystadt and Schumacher 2012).

The study tests the hypothesis that increased precipitation, extreme temperatures, and an increase in occurrences of weather shocks are associated with an increase in the probability of workers' migrating from rural areas to other rural or urban areas. However, the effect is not significant for workers migrating from the urban areas. The second hypothesis tested is that the effect of increased precipitation, extreme temperatures, and increases in occurrences of weather shocks on migration is significant for workers from wealthy households but is not significant for workers from non-wealthy households.

The study uses the UBOS 2009/10 and UBOS 2013/14 micro-level household survey data and weather data to explore the relationships between weather variability and migration with the unit of analysis being the individual worker. The data was observed for two time periods. The first survey conducted in 2009 was assumed to be the year before migration, together with data from the second survey was that collected in 2013 and 2014, which is the period after which migration is observed. A migrant was defined as a worker living in a rural area, aged between 16 and 70 years at the time of the first survey conducted in 2009, whose place of residence changed between the first survey period and the second. A cross-sectional analysis was used to exploit the spatial variation in weather conditions for different locations to explain migration decisions. Marginal effects from a binary logit model were used to examine the likelihood that a worker would migrate from a rural or urban area. The results show that an increase in exposures to extreme temperatures during the crop production seasons had a positive and statistically significant effect on the likelihood of migration of workers whereas an increase in exposures to the average or median temperatures had a negative and statistically significant effect. The results imply that gradual increases in exposures to temperature above the averages are likely to be marked with mobility of labor from the rural areas but with no significant effect on worker migration from the urban areas. The results also showed that an increase in extreme weather events such as floods and landslides had no significant effect on the migration of workers. The findings from this research can be useful for informing policies associated with labor mobility, population redistribution, and building resilience against extreme changes in weather. The rest of the paper is structured as follows; the next section presents a review of literature that summarizes studies that are related to migration and weather variability, the third section presents the empirical framework used for this study, whereas section four, five and six present the results, discussions, and policy recommendations, respectively.

1.2 Review of literature

Geographic and occupational migration of labor is one of the characteristics of structural transformation and contributes to economic development through the transfer of human capital and redistribution of the population. Within developing countries, rates of internal and international mobility of labor are increasing, making migration one of the important issues for development and policy consideration. Different theories have been formulated to explain the reasons why workers migrate. Neoclassical theories show that workers compare their current earnings to those that they could potentially earn in a different location or with a different job and will migrate if the wage difference is significant (Schultz 1962, Sjaastad 1962, and Todaro 1969). Human capital theory is based on the same assumptions as neoclassical theories, but posits selectivity in migration based on individual characteristics and costs of migration (Borjas 1989). On the other hand, the New Economic Theory of Labor Migration views migration as a risk-reduction strategy for the worker and household and that workers' decisions to migrate are not done individually, rather are influenced by the household and society (Stark and Bloom 1985). Bohra-Mishra et al. (2017) show that wage and non-wage factors such as access to amenities and social networks affect migration. One of the non-wage factors that is increasingly gaining attention is the effects of climate and weather changes in influencing migration decisions.

Studies that examined the relationship between weather anomalies and migration made use of both micro- and macro-economic analyses, both of which use multivariate approaches to account for potential confounding variables. Micro-level analyses typically investigate migration decisions for an individual or an entire household to locations within the borders of a country by linking household survey data to climate data for specific locations. However, some studies show that there is a significant relationship between climatic factors and migration whereas others do not. For example, Grace et al. (2018) examined the effect of rainfall variability on rural migration in Malian villages and found that whereas rainfall variability affected the incomes of subsistence farmers, it had no significant impact on migration decisions and this was attributed to the inability to afford migration costs. On the other hand, Henry, Schoumaker and Beauchemin (2004) found that precipitation had a significant effect on the migration of households in Burkina Faso. Bohra-Mishra et al. (2017) also used a micro-level study in Indonesia to investigate how variations in temperature affect permanent migration of entire households, the results showed that temperature has a nonlinear effect on migration, such that a rise in temperature above 25^{o}C was related to an increase in outmigration.

The studies that used macroeconomic analyses examined the effect of climate and weather variability on international and cross border migration. Macroeconomic analyses typically investigate long term effects of climate change by linking migration data to long term averages for weather variables usually measured at county, state or country level. Cai et al. (2016) investigated the effects of weather variability on international migration flows and the results showed that temperature has a positive and statistically significant effect on out-migration but this was only true for countries that are dependent on agriculture. A similar finding was found by Coniglio and Pesce (2015), Bohra-Mishra, Oppenheimer, and Hsiang (2014) & Feng, Krueger, and Oppenheimer (2010) who conducted cross country comparisons and found a significant relationship between weather variables and international migration, but the relationship was significant for countries whose economies relied heavily on agriculture and also those that had low levels of development measured by their Gross Domestic Product (GDP). Other studies such as Bohra-Mishra et al. (2017), and Thiede, Gray and Mueller (2016) examined how extreme weather events such as floods, earthquakes and landslides affect migration decisions and the results suggested that weather shocks had negative significant effect on internal or international migration. This is because weather shocks reduce a household’s ability to finance costs of relocation through their effect on yield, financial loss and loss of assets. Besides, social bonds created after a disaster reduces households’ incentive to migrate (Bohra-Mishra, Oppenheimer and Hsiang 2014).

In summary, the literature shows evidence that weather and climate variability affect internal as well as international migration. However, the effects of rainfall variations are often weak relative to temperature changes and there is not a great deal of evidence to demonstrate that weather shocks affect migration of labor. Also, the magnitude of the effects is not generalizable since the socioeconomic conditions and severity of weather conditions differ for different countries and also different locations within a country. This study, therefore, contributes to the literature on weather-induced migration by exploiting differences in weather conditions across locations to explain migration decisions for workers in both rural and urban areas. However, temperatures in a given location may not be completely exogenous, since there are possible interactions of temperature with precipitation. This study, therefore, estimates the effect of precipitation and extreme temperatures while taking into account the possible effect of precipitation in mitigating the effect of temperature extremes.

1.3 Theoretical framework

This study was based on the human capital theory of migration, with the assumption that a worker n that faces J migration possibilities will choose alternative j if it has the highest utility, where $j = 1,2 \ldots J$. The theory assumes that workers' intentions for migration are not only based on income differentials, but also leisure and amenities. In continuous time, the optimization problem for the worker can be summarized by the Hamiltonian equation (1.1) where a worker's discounted utility $e^{-\rho t}U(.)$ is derived from the consumption derived from income (I) and leisure (L). However, in a predominantly agricultural economy, income is a function of weather variables (T), location-specific factors (R), workers' observable characteristics such as education (X), as well as unobservable factors (ε) such as bargaining power and innovativeness i.e. $I = f(T, R, X)$. A worker incurs costs of migration (C_{ijt}) that may be monetary or non-monetary.

$$H_{nij} = \int_0^t \Big(U_{njt}\big(I_{njt}(T,R,X), L_{jt}\big) - U_{nit}\big(I_{it}(T,R,X), L_{it}\big)\Big) e^{-\rho t} dt - C_{ijt} > 0 \tag{1.1}$$

H_{nij} is the net return of migration between locations i and j, U_{njt} is the utility obtained if a worker n moves to location *j* which is a possible destination of the migrant in time *t*, U_{nit} is the utility that the worker obtains from staying in the current location i in time *t*, ρ is the discount rate and C_{ij} are the costs of migration between i and j. For short-term migration, the Hamiltonian equation can be simplified to a two-period migration model with a discount rate of zero and no uncertainty as shown in equation (1.2). In this case, a worker migrates from area i to *j* if $H_{nij} \geq 0$ and this requires that

$$U_{njt}\left(I_{jt}(T,R,X),L_{njt}\right) - U_{nit}(I_{nit}(T,R,X),L_{nit}) - C_{ijt}(D,M_t,S_t) > 0 \qquad (1.2)$$

Equation (1.2) shows that a worker migrates if the net utility is positive. Since migration involves monetary costs, it implies that a worker must hold a minimum amount of capital to have migration as an option. Therefore, a migration outcome is observed if the earning is obtained from the current occupation in location i is high enough to finance the monetary costs of migration as shown in equation (1.3).

$$I_{nit} - C_{ijt} > 0 \qquad (1.3)$$

The assumption is that the adverse effect of weather changes on productivity and earnings creates an incentive for workers to migrate. However, it is possible that the adverse effects of weather variability further impoverish low wealth households, decreasing their ability to afford migration costs. With low earnings and limited access to formal credit and physical assets, migration is not an option for workers from extremely poor households. On the contrary, workers from high wealth households can afford financial costs of migration from their earnings or the sale of their assets. It is therefore plausible that migrants are not a random sample, but rather are self–selected based on their human capital and their ability to afford the monetary cost of migration. The migration of workers, therefore, depends on weather conditions, worker characteristics, household characteristics, and location characteristics.

1.4 Model choice and assumptions

From Random Utility Theory, the utility U_n that a worker n derives from migrating can be decomposed into a deterministic component V_n that depends on unknown parameters β, K observed characteristics for weather variables, location, workers observable characteristics, and also an unobserved random component ε_n. Therefore, the utility for an individual *n* can be represented as $U_{nit} = V_{nit} + \varepsilon_{nit} = \sum_{k=1}^{K} \beta_{ik} X_{nik} + \varepsilon_{nit}$ for the current locality and $U_{njt} = V_{njt} + \varepsilon_{njt} = \sum_{k=1}^{K} \beta_{jk} X_{njk} + \varepsilon_{njt}$ for the potential locality.

To identify the effect of extreme weather changes on labor migration, a cross-sectional analysis was conducted by exploiting the heterogeneity in weather conditions for different locations of the country. Workers are faced with a decision of whether to migrate or not and therefore their choices are modeled using a binary logit framework shown in equation (1.4). The binary logit model was based on the assumptions of independence of observations, the linearity of independent variables and low or no correlation amongst the independent variables.

$$P_{nj} = Prob(Y_n = j) = ln\left(\frac{p}{1-p}\right) \tag{1.4}$$

$$= \frac{exp(\sum_{k=1}^{K} \beta_{ik} X_{nik} + \varepsilon_{nit})}{1 + exp(\sum_{k=1}^{K} \beta_{ik} X_{nik} + \varepsilon_{nit})}$$

The econometric model used for estimation is as shown in equation (1.5). The weather anomalies are captured by variables for temperature, precipitation, and weather shock and it was assumed that weather variability for each location is exogenous and is uncorrelated with the error term. Individual characteristics (X_{nt}) that affect migration such as earnings before migration, age, sex, education and household characteristics such as household size and wealth status were included as control variables. The error term e_{int} accounts for the factors that affect the likelihood of migration but are not included in the model.

$$\begin{aligned} Prob(Y_n = j) &= ln\left(\frac{p}{1-p}\right) \\ &= \alpha_0 + \gamma_1 T_{i1} + \gamma_2 T_{i2} + \gamma_3 T_{i3} + \gamma_4 P_i + \gamma_5 P_i^2 \\ &+ \gamma_6 T_{i1} * P_i + \gamma_7 T_{i2} * P_i + \gamma_8 T_{i3} * P_i + \gamma_9 WS_i \\ &+ \sum_{k=1}^{K} \alpha_k X_n + e_{in} \end{aligned} \tag{1.5}$$

The variable T_i represents temperature for location $i,$ measured by the number of days of exposures to temperature ranges above the average, whereas P_i represents precipitation both of which are specific for location i are observed for the time t between the years 2010 and 2012. To capture nonlinear effects, a quadratic specification for the precipitation variable was used to capture the effect of extreme precipitation on the likelihood of migration. Weather shocks (*WS*) were also included to capture the effect of disasters such as floods and landslides on the relocation of workers. Therefore, the coefficients of interest are γ_1, γ_2 and γ_3 that corresponds to temperature intervals, γ_4 and γ_5 that correspond to precipitation and precipitation squared respectively, $\gamma_6, \gamma_7, \gamma_8$ that correspond to the interactions between precipitation and temperature, and γ_9 that corresponds to weather shocks.

Estimation was performed using the maximum likelihood method. However, the parameters of the logit models are not directly interpretable. Therefore, marginal effects were estimated, whereby for an individual *n*, the marginal effect of a change in the k^{th} regressor on the probability that alternative *j* is the outcome was computed as shown in equation (1.6).

$$ME_{njk} = \frac{\partial Pr(y_n = j)}{\partial X_{nk}} = \frac{\partial F_j(X_n, \theta)}{\partial X_{nk}} \tag{1.6}$$

1.5 Data

The data used for analysis was obtained from the national household surveys conducted by the Uganda National Bureau of Statistics, and these can be obtained from UBOS (2011) and UBOS (2014). The UBOS 2011 and 2014 data were collected from thirty-nine districts located in four regions of Uganda and therefore the sample is representative of the whole country. The data contained information on location, individual characteristics, migration, employment, and experience with weather-induced disasters respectively. The sample was comprised of workers aged 16 to 70 years, not enrolled in school and with complete information regarding their location at the time of the 2009/2010 survey and their location during the 2013/14 survey. A migrant was defined as an individual who declared their place of residence in the year 2009 to be different from his or her residence during the 2013/14 survey.

Weather data for the time between 2009 and 2011 were obtained from the National Climatic Data Center's (NCDC) Global Summary of the Day archive, which contained daily temperatures and precipitation data from 11 weather stations located throughout the country. Weather data were matched to the initial location before migration. Given that wage earnings are closely tied to agricultural production, the temperature and precipitation measurements that were considered for this analysis are those that correspond to the critical periods for growing seasonal crops. Uganda experiences two growing seasons in a year, with the first season starting in February and ending in May, and the second season starting August to December. Hourly temperature data was then aggregated for the entire growing season that is determined from the crop calendar for major staple crops that include corn, beans, peas, potatoes. The temperature variables were measured using the concept of growing degree days. Growing degree days measure the temperature based on the accumulated days of exposure to temperatures above a base temperature. Base temperature is the minimum temperature required for crop growth defined here to be 10^{o}C. Precipitation was measured based on the accumulated rainfall within the major crop growing seasons.

To examine whether migration decisions depend on the wealth status of the worker, Principal Component Analysis (PCA) was used to construct an index of wealth from the data provided on ownership of durable assets. The PCA is a mathematical procedure that transforms several possibly correlated variables into a smaller number of uncorrelated variables called principal components (Jolliffe 2002). The components are obtained from weights obtained through statistical techniques. Different assets were accorded to different weights and the wealth index for individual n, A_n was obtained as shown in equation (1.7). The variable a_{nk} is the value of asset k, $\bar{a}_k$ is the sample mean, S_k is the sample standard deviation and f_k are weights that are associated with the first principal component (Jolliffe 2002).

$$A_n = \sum_k f_k \frac{(a_{nk} - \bar{a}_k)}{S_k} \tag{1.7}$$

The wealth index was estimated for ten assets listed in the survey, including: livestock, cellphone, house, radios, land, television, motorcycle, solar panel, bicycle and a vehicle as shown in appendix A.1. All variables were first dichotomized to indicate ownership for each asset, and then weights computed for each asset. To take into consideration, the distribution of assets in rural and urban areas, weights were estimated separately for urban and rural areas and then a relative wealth variable was created in the pooled data set. The weights were assigned such that assets that are common in all households are assigned a low weight and those that are not are assigned a higher weight. For example, since almost all households in urban areas owned a television set, it was given a low weight, implying that owning a television does very little to increase ones' wealth index. In contrast, a mobile phone weighed more heavily and was a principal component since not many households owned a mobile phone set and it was also strongly correlated with ownership of other assets. The first principal component, therefore, accounts for much of the variability in the data, and each succeeding component accounts or the remaining variability.

1.6 Results and discussion

1.6.1 Characteristics of the respondents

The characteristics of the respondents are presented in table 1.1, with the columns showing the results for the whole sample, workers who never migrated, and those who migrated. Quantitative variables were summarized using means and the statistical difference between the migrant and non-migrant workers was obtained using a t-test. Categorical variables were summarized using counts and percentages and the statistical differences between the migrant and non-migrant workers were obtained by using a Pearson chi-squares test. The *p*-values for the t-test and chi-square tests are presented in the fourth column.

The mean for the age of the respondents was 37.15 years with no statistically significant difference in the mean ages between the migrant and non-migrant workers. Migrant workers have a lower mean age of 36.52years as compared to the non-migrant workers with a mean age of 37.37. The results also showed that the mean wages earned before migration were an equivalent of 148.76 US Dollars, with the mean earnings for workers who migrated being higher than that of the ones that did not, although the difference is not statistically significant. The minimum wage earned was zero for workers who were not employed before migration, and also for those that were doing volunteer jobs. The mean household size was 6 persons and this was the same for the households of migrant and non-migrant workers.

The results showed that for both the workers that migrated and those that did not, the percentage of workers in the high wealth group was higher than that in the low wealth group. The chi-square test showed a statistically significant difference in wealth status, between workers that migrated and those that did not, at 10 percent level. The results further showed that the sample was characterized by a large number of respondents with low education levels, with the majority obtaining primary and ordinary level education. However, there was no statistically significant difference in the education levels of workers that migrated and those that did not at the five percent level. The sample comprised of a large number of workers who were male and those that were married, although there was no statistically significant difference between the workers that migrated and those that did not in these categories.

Table 1.1 Characteristics of respondents

Quantitative characteristics	Combined (n=1772)	Non-migrants (n=1318)	Migrants (n=454)	t-test
Mean age (Years)	37.15	37.37	36.52	1.2216
Minimum age	16	16	16	
Maximum age	70	70	70	0.222
Standard Deviation of age	12.83	12.8	12.9	
Mean Wage before migration (USD)	148.76	146.67	154.83	-0.244
Minimum wage	0	0	0	
Maximum wage	12048.88	12048.9	9446.33	0.8073
Standard Deviation of wage	614.3	618.94	601.27	
Mean household size before migration (USD)	6	6	6	
Minimum household size	1	1	1	0.9027
Maximum household size	17	17	14	
Standard Deviation of household size	3	3	4	0.3668

Qualitative characteristics	Count	Percentage	Percentage	Chi-square
Weather shock				
No shock	1477	83.08	84.14	0.601
Shock	295	16.92	16.08	
Wealth group				
Low wealth	643	37.86	31.72	0.091
High wealth	1129	62.14	68.28	
Sex				
Female	845	48.25	46.04	0.414
Male	927	51.75	53.96	
Marital status				
Married	476	72.69	74.45	0.465
Not married	1296	27.31	25.55	
Education level				
Primary level	1313	75.19	70.93	0.129
Ordinary level	345	18.44	22.47	
High school level	30	1.90	1.10	
Tertiary and higher	84	4.48	5.51	
Main occupation				
Non-farmer	1612	91.05	90.75	0.848
Farmers	160	8.95	9.25	

1.6.2 Weather variables

The results for weather variables are summarized in table 1.2, and these show that the mean monthly precipitation received during was 30.92 inches. The average temperature experienced by the sample during the critical crop production period season was 23.04^{o}C, whereas the minimum and maximum temperatures were 16.55^{o}C and 29.64^{o}C respectively. To capture the different temperature ranges, we constructed temperature intervals at 3 levels: less than 21^{o}C, between 21 to 29^{o}C, and temperatures greater than 29^{o}C.The categories less than 21^oC and those greater than 29^oC were considered to be the temperature anomalies.

Table 1.2 Summary statistics for monthly weather variables

	Mean	Standard Deviation	Minimum	Maximum
Minimum Temperature (^oC)	18.00	1.19	16.55	19.78
Maximum Temperature (^oC)	28.08	0.95	26.62	29.64
Average Temperature (^oC)	23.04	0.96	21.58	24.45
Precipitation (Inches)	30.92	14.12	1.02	46.23

1.6.3 Regression results

The effect of weather anomalies on labor migration was analyzed using a binary logit model and the results for the marginal effects at the mean are presented in table 1.3. Models 1and 2 show the results for the whole sample, models 3 and 4 show the results for workers based on their locations before migration, and this was in rural and urban areas respectively. Models 5 and 6 show the results for workers based on their main occupation before migration whereby model 5 that is labeled non-farm shows results for workers that were not employed on farms such as traders and transporters. Model 6 that is labelled farm shows results for workers that were employed on farms as farmers or casual laborers. Also, model 1 shows the results when only weather variables are used as regressors, whereas the other models show the results when control variables are added to the model. The results show that adding control variables such as worker and household characteristics improved the model fit as shown by the likelihood ratio. A Wald test for model misspecification was also conducted to check the validity of including quadratic variables in the model. The Wald test was based on the null hypothesis that the coefficient for the quadratic age and precipitation variables were no different from zero. However, the results showed a Wald statistic of 40.19 and a p-value significant at 1 percent, leading to a rejection of the null hypothesis. The binary logit model was therefore better specified with the inclusion of the quadratic variables.

Table 1.3 Marginal effects for binary logit models

(Dependent variable Y = Whether or not a worker migrated)	Model 1 All	Model 2 All	**Based on location** Model 3 Rural	Model 4 Urban	**Based on occupation** Model 5 Non-farm	Model 6 Farm
Precipitation (Inches)	0.0340	0.0340	0.0409	0.0040	0.0299	0.0269
	(0.0045)***	(0.0045)***	(0.0050)***	(0.0058)	(0.0043)***	(0.0118)**
Temperatures <21°C	0.0019	0.0019	0.0023	0.0003	0.0018	0.0016
	(0.0002)***	(0.0002)***	(0.0003)***	(0.0004)	(0.0002)***	(0.0006)**
Temperatures 21 to 29°C	-0.0177	-0.0172	-0.0205	-0.0028	-0.0162	-0.0144
	(0.0021)***	(0.0021)***	(0.0024)***	(0.0036)	(0.0022)***	(0.0056)**
Temperatures >21°C	0.0566	0.0553	0.0655	0.0108	0.0521	0.0491
	(0.0063)***	(0.0063)***	(0.0070)***	(0.0105)	(0.0064)***	(0.0177)***
Weather shock (Base=No shock)	-0.0091	-0.0082	-0.0035	-0.0111	-0.0266	0.2049
	(0.0268)	(0.0269)	(0.0309)	(0.0460)	(0.0291)	(0.0810)**
Wealth group (Base=Low wealth group)		0.0387	0.0247	-0.0406	0.0266	0.1080
		(0.0213)*	(0.0244)	(0.0386)	(0.0229)	(0.0665)
Age (Complete years)		-0.0017	-0.0022	0.0008	-0.0023	0.0061
		(0.0010)*	(0.0011)**	(0.0016)	(0.0010)**	(0.0037)*
Sex (Base=Female)		-0.0088	-0.0078	0.0376	-0.0045	-0.2434
		(0.0208)	(0.0237)	(0.0382)	(0.0215)	(0.0908)***
Marital status (Base=Not married)		0.0374	0.0462	-0.0361	0.0607	-0.1450
		(0.0245)	(0.0274)*	(0.0486)	(0.0274)**	(0.0798)*
Education level (Base=Primary level)						
Ordinary level		0.0427	0.0647	0.0564	0.0578	-0.1579
		(0.0265)	(0.0313)**	(0.0478)	(0.0259)**	(0.0729)**
High school level		-0.0846	-0.1502	0.0923	-0.0843	

	(0.0681)	(0.0843)*	(0.1041)	(0.0913)	
Tertiary and higher	0.0619	0.2061	-0.0613	0.0588	0.2593
	(0.0557)	(0.0766)***	(0.0532)	(0.0519)	(0.2251)
Farmer (base =Off-farm employment)	0.0068	0.0127	0.0304		
	(0.0361)	(0.0413)	(0.0826)		
Household size	-0.0032	-0.0044	0.0008	-0.0039	0.0083
	(0.0034)	(0.0040)	(0.0059)	(0.0036)	(0.0126)
Wages before migration (US Dollars)	0.0012	0.0081	0.0251	0.0024	0.0351
	(0.0163)	(0.0277)	(0.0145)*	(0.0162)	(0.0723)
Sample size	1772	1446	326	1612.0000	160.0000
Wald chi-square	128.14	136.82	74.70	118.2800	28.6400
Probability value	0.0000	0.0000	0.0000	0.0000	0.0179
Pseudo R-squared	0.0711	0.0936	0.0707	0.0728	0.2223
Log pseudo likelihood	-936.6360	-780.6160	-121.5950	-849.5160	-71.6289

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

The results showed that the non-weather factors that had a significant effect on the migration of labor from rural areas included the age and education status of the migrant. An increase in age by one year reduces the likelihood of migration from the rural areas by 0.2 percent. On the other hand, workers that have high school education are less likely to migrate as compared to those with primary or no education. However, workers with ordinary level education and those with tertiary education more likely to migrate as compared to those with primary education. These results suggest that young workers and those with very low or very high levels of education are more likely to migrate from the rural areas.

Also, the results for the binary logit regression in table 1.3 show a nonlinear relationship of temperature and precipitation on the likelihood of migration and these were significant for workers in rural areas. The results indicate that an increase in precipitation during the crop production season increases the likelihood of worker migration from the rural areas. However, the results for the predictive margins for precipitation presented in figure 1.1 show that the effect of increased precipitation on the likelihood of migration is non-linear, with precipitation exceeding 25 inches per month resulting in a reduction in the likelihood of migration. The precipitation amounts that result in a reduction in the likelihood of migration correspond to the optimal precipitation amounts for growing seasonal staple food crops like maize, sweet potatoes and beans and this is between 25 and 50 inches per season. Therefore, an increase in precipitation to amounts less than 25 inches will increase the likelihood of migration, however, precipitation amounts greater than 25 inches that favor crop growth will lead to a reduction in the likelihood of migration.

Increased precipitation is associated with an increase in productivity and wage earnings, especially for workers employed on farms (Alem, Maurel and Millock 2017) thereby reducing the incentive to relocate to other areas.

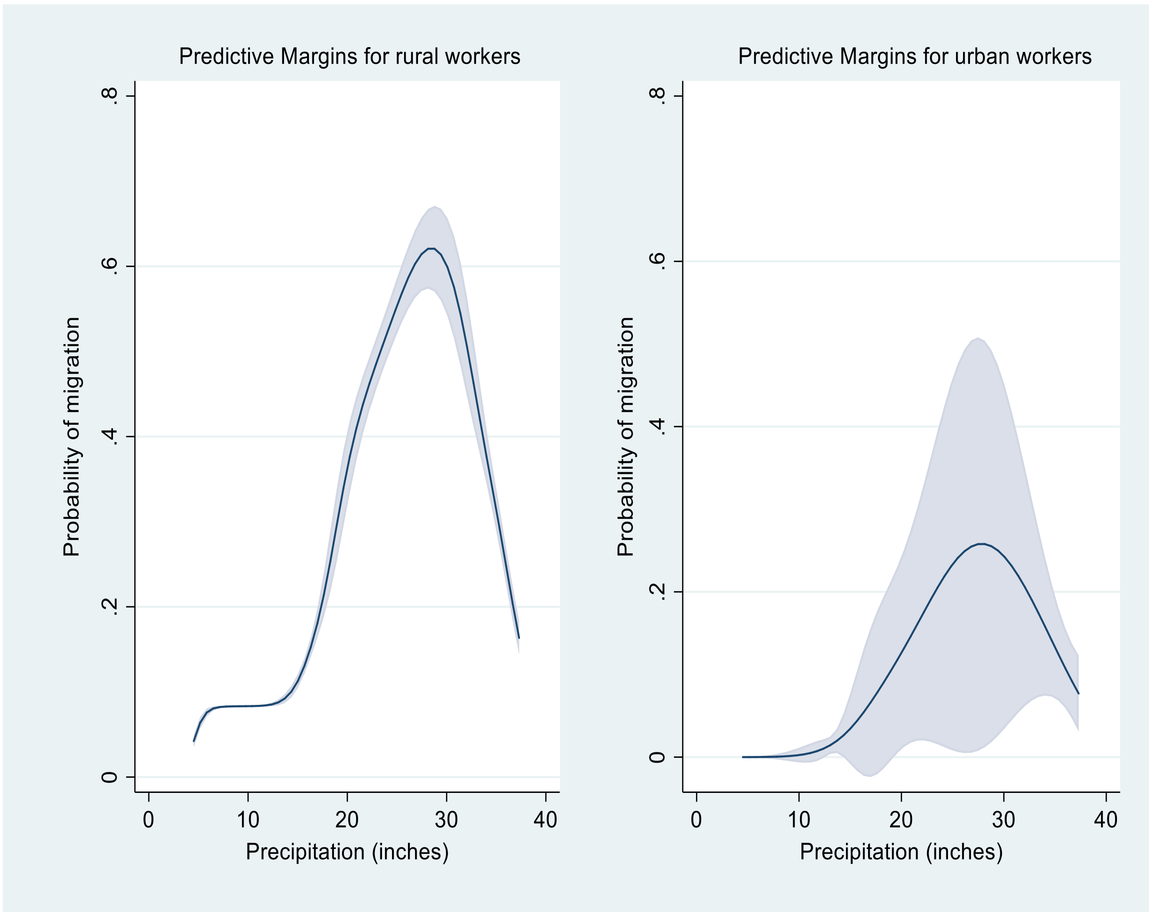

Figure 1.1 Predicted margins for precipitation increase

The results in table A.1 show a significant and nonlinear relationship between temperature and the likelihood of migration from rural areas. An increase in exposures to temperature anomalies within the ranges less than 21^{o}C and those greater than 29^{o}C increase the likelihood of migration whereas increased exposures to normal temperatures between 21°C and 29°C significantly reduce the likelihood of migration from the rural areas. Exposures to moderate temperatures in the range of 21°C to 29°C, which also corresponds to temperature averages for most parts of the country significantly reduces the likelihood of migration. Moderate temperatures between 21°C and 29°C are optimal for the production of staple food crops such as maize, beans, coffee, potatoes and cassava. If temperatures are conducive for production and have no adverse effect on the availability of resources such as water, the incentive for migration is low.

Using the piecewise linear regression model that divides the logistic regression into linear segments, the effect of temperature increases was obtained and is figure 1.2 with the first graph showing the results for the whole sample whereas the second and third show the results for the workers in rural and urban area respectively. The graphs show that exposure to temperatures less than 21°C increases the likelihood of migration whereas exposure to temperatures between 21 and 29°C is associated with a reduction in the likelihood of migration. On the other hand, exposures to extreme temperatures greater than 29°C are associated with a large and significant increase in the likelihood of migration. Extreme temperatures can induce migration through their adverse effect on crop productivity (Cattaneo and Peri 2016; Feng, Oppenheimer, and Schlenker 2015) and also through drying up of surface water sources. Extreme temperatures therefore may induce workers to migrate to locations in search of employment that is less reliant on weather or to places with better weather conditions.

For workers in the urban areas, the effect of temperature on the likelihood of migration was not significant as shown in table 1.3, implying that temperature anomalies have no significant effect on worker migration from urban areas. Figure 1.2 also shows that the marginal effect of temperature on the likelihood of migration of workers in the urban areas with large confidence intervals.

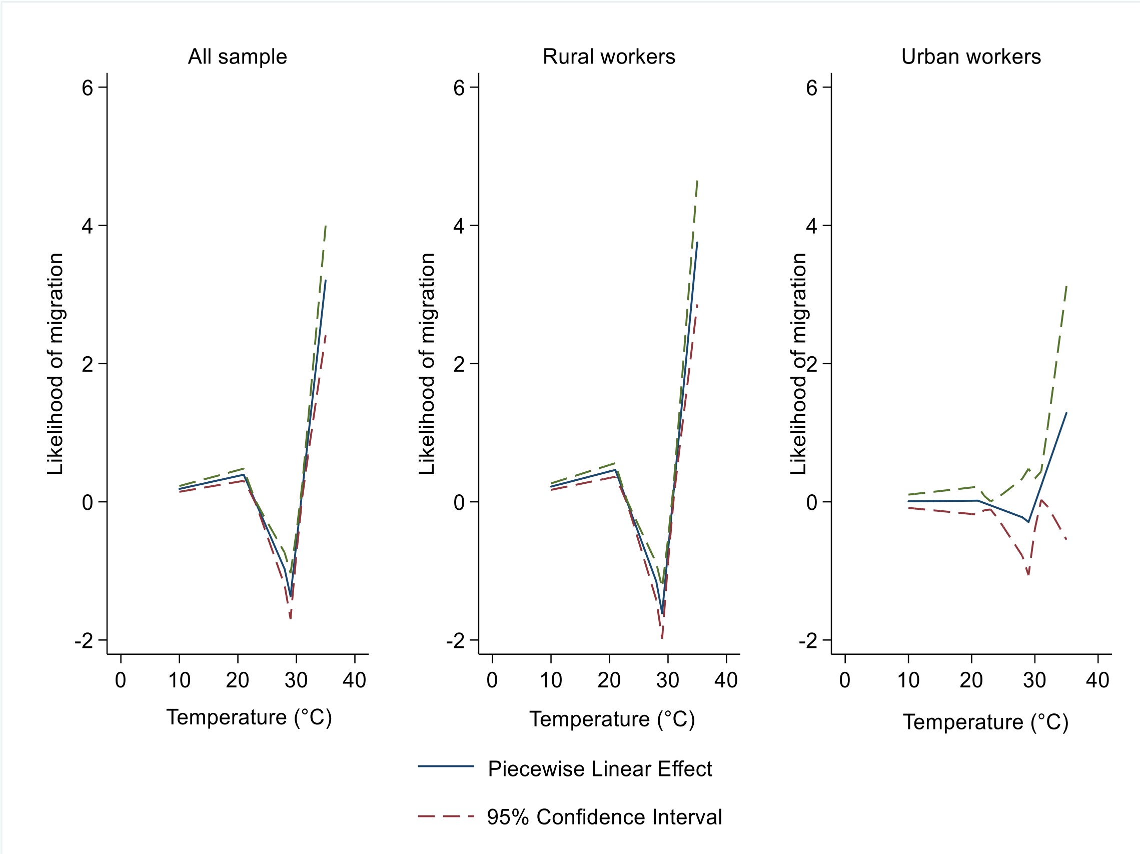

Figure 1.2 Effect of temperature increase by location

The results also showed that wealth status had no significant effect on the likelihood of labor migration. The same result can be seen when the sample is disaggregated by wealth status as shown in appendix A.2. The results show that the effect of extreme temperatures on the likelihood of migration is positive and significant for all wealth groups. These results contrast the findings by Cattaneo & Peri (2016), who showed that wealth is a significant determinant of migration, with migrants from middle- and high-income countries having a higher likelihood of migration as compared to those from the low-income countries.

The sample of workers was classified into two categories; the first category was that of workers employed on farms, whereas the second was that of workers employed in the non-farm sector but with informal employment such as food processing and trading. The results show that the marginal effects of temperature increase on the likelihood of migration were more significant for workers employed in the non-farm sector as compared to those employed as farmers as shown by the size of the confidence intervals in figure 1.3. In Uganda, the majority of the farmers have low levels of education and with farming as their only source of livelihood. Their migration possibilities are therefore limited by the fact that they are not able to transfer their skills to other occupations when there are temperature extremes. Besides, many since most of the farmers are landowners, they value the security of their land and are therefore not move to other locations.

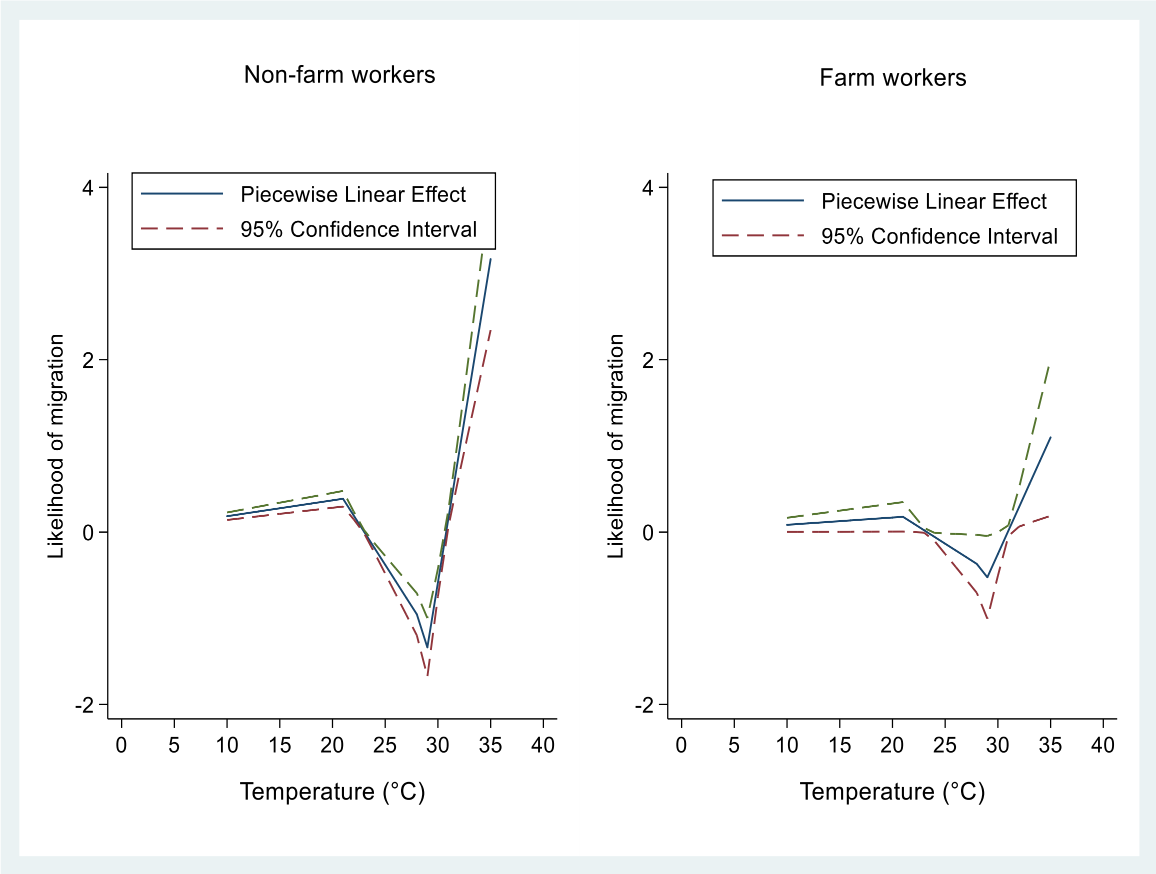

Figure 1.3 Effect of temperature increase by occupation

1.7 Summary and conclusions

The purpose of this research was to examine the effect of weather anomalies on the likelihood of worker migration from rural and urban areas. The results showed that the effect of increased precipitation was significant and positive for worker migration from rural areas. The results for all model specifications show that the effect of extreme temperature on the likelihood of migration is significant for worker migration from rural areas but not the urban areas. These results show the importance of weather variability in affecting rural economic activity which is mainly agricultural. The results also showed that wealth status was not significant in influencing migration decisions. Therefore, the hypothesis that wealth migration depends on wealth status was rejected, implying that the marginal effects of changes in temperature and precipitation on the likelihood of migration were significant for workers in the high wealth status and those in the low wealth status.

The results from this study indicate that if no resilience or mitigation mechanisms are put in place, increased precipitation and exposure to extreme temperatures could result into a redistribution of labor in rural areas, that may be characterized by the out-migration of the young workers leaving the older who may be less productive. The out-migration of labor from rural areas can increase the cost of labor for production given that the level of mechanization is still very low. The study, therefore, recommends that strategies to be put in place that increase the resilience of workers in rural areas, such as those that make them less dependent on occupations that are susceptible to weather changes. This could be through the promotion of education and skills training that can enable them to diversify employment. Also, policies that promote environmental protection should be implemented, as well as investment in infrastructure such as tarmac roads, markets and water sources that are not significantly affected by weather can go a long way in reducing uncertainties associated with rural wage earnings and employment that could otherwise lead to mobility of labor.

This study examined the effect of weather variability on internal migration of labor, based on short-term changes in temperature and precipitation. I, therefore, recommend for the analysis to be extended to examine the effects based on long-term weather and migration data. Also, further studies need to be conducted to examine the effects of climate and weather changes on cross-border migration.

Chapter 2 - Critical Temperatures and Viability of Shade Plants for the Reduction of Heat Stress for Coffee Production in Uganda

2.1 Introduction

Increasing temperatures and erratic rainfall are the threats to improvements in crop productivity. It is projected that temperatures in Uganda will continue to increase by 1.5^{o}C in 2030 and by 4.3^{o}C in 2080 with longer dry periods, shorter rainfall periods and periodic drought (Niang et al. 2014). While the rainfall mean quantity might not drastically change its distribution is expected to become more erratic (Asten et al. 2011). When faced with changes in the timing and intensity of rainfall or increased temperatures, farmers can mitigate the possible risk of crop failure by adjusting their planting period or switching to more drought-resistant seasonal crops. However, with perennial crops, such seasonal adjustments are not feasible in the short term since their maturation period and lifecycle takes several years. Given that there is limited access to water and technologies for irrigation, the effect of changing weather patterns on yield for perennial crops such as coffee is severe. Coffee is an important foreign exchange earner in Uganda, accounting for 52 percent of the agricultural export earnings (UBOS 2017). Coffee is also an important cash crop and source of income for most of the rural farming community.

Increasing temperatures and erratic rainfall patterns remain one of the major threats to improvements in coffee productivity. Increasing temperatures affect coffee production directly by increased rates of evapotranspiration, reduced quantities and quality of berries

(DaMatta, et al. 2007; Haggar and Schepp 2012) and indirectly by creating an environment through which pests and diseases thrive (Jassogne et al. 2014). Alemu and Dufera (2017) show that the spread of the coffee berry borer and coffee leaf rust disease increases as temperatures increase. Erratic rainfall patterns also affect the quality and biological processes for berry development (DaMatta et al. 2007; Drinnan and Menzel 1995), whereas excess rainfall leads to erosion of soil and nutrients if there are no measures to effectively control water runoff.

Intercropping coffee with shade trees or plants is one of the practices through which heat stress from increasing temperatures can be reduced, but with limited empirical evidence to show the effectiveness in mitigating extreme heat (Asten et al. 2011; Jassogne et al. 2014). Alemu and Dufera (2017) show that some shade trees compete with coffee for water, but less competition is observed with banana plants. Banana plants are more resistant to extreme heat and their canopy provides shade that controls the heat stress on coffee, reducing the spread of diseases and also improving the quality of coffee beans (Alemu and Dufera 2017; Asten et al. 2011). In Uganda, the common farming practice for coffee is the single cropping and the coffee-banana intercropping, as shown in figure 2.1. Some studies examined the effect of changing weather patterns on coffee yield, for example, Rising (2016) and Sachs et al. (2015) examined the effect of increasing temperatures on Robusta coffee and they found that temperatures above 32^{o}C result in yield losses. Davis et al. (2012) showed that temperatures between 28^{o}C and 30^{o}C reduce flower bud formation and fruit production for Arabica coffee in Ethiopia. This implies that temperature extremes reduce both the flower formations and the production of fruits or berries. Rising (2016) shows that the effect of temperature extremes on productivity depends on the variety of coffee grown, whereby the optimal temperatures for Robusta coffee are between 22^{o}C and 30^{o}C and for Arabica coffee, they range between 18^{o}C and 22^{o}C. Given that these studies analyzed effects for single-cropped coffee farms, empirical analysis for the effects of temperature and precipitation extremes for intercropped coffee farms is limited.

Therefore, the objective of this research is to examine the critical temperatures for yield reduction of coffee in Uganda, and examine whether the effects on yield differ for single cropped and intercropped coffee plots. The hypothesis tested is that the yield reduction from extreme temperature is lower for intercropped plots as compared to the single cropped coffee plots. Following the seasonal calendar, weather data was used to derive the amount of precipitation as well as the number of days for which temperatures are above the average, and summed across all days in the growing season and estimated for specific locations. Weather data was combined with plot-level data from which the effects were identified from the spatial variation of weather variables. Both cross-sectional and panel regression models were used to estimate the effects with the assumption that weather variables are exogenous and are not correlated with any control variables used in the regression models. The results show that there are nonlinear effects of temperature and precipitation with extreme temperatures greater than 28^{o}C, resulting in significant reductions in yield. Also, an increase in the intensity of intercropping has a positive and significant effect on yield, but the yield reduction from extreme temperatures was lower with intercropped plots as compared to single cropped plots. The results are robust to alternative specifications of models as shown in the fourth section of this paper. The rest of the paper is structured as follows; the second section presents key findings from related literature whereas the third section presents the description of data and empirical methods used for analysis. The last section presents a summary of results and policy implications.

Coffee farming system **Coffee-Banana farming system**

Figure 2.1 Coffee farming systems in Uganda

2.2 Previous studies

Precipitation and air temperature are important requirements for crop growth and they affect crop productivity. Other factors that affect productivity are management practices, the prevalence of pests and diseases, and soil quality. The type of soil used for production also determines how much a crop is affected by extreme heat or limited rainfall. DaMatta et al. (2007) and Sachs et al. (2015) showed that soil properties determine the water retention capacity, and therefore farms with sandy soils are more affected compared to those with clay soils that have a higher retention capacity.

Several methods have been used to empirically estimate the effect of extreme heat and precipitation on crop yield, most of which relied on macro-level data. Burke and Emerick (2016), Cabas, Weersink and Olale (2010) and Wang et al. (2015) used aggregate data to examine the effects of temperature extremes on yield and the results are useful for designing strategies for adaptation at the country, state, county or regional level. However, using aggregate data does not take into consideration the heterogeneity in weather conditions within a country nor response strategies that farmers may use to mitigate negative effects at the farm level (Salvatore, Marcella and Mahmud 2011). Aggregate data also makes use of average temperatures and precipitation variables specified over time and this may underestimate the marginal yield impact of extremes by offsetting high temperatures with lower ones (Robertson et al. 2013). Alternative measures for temperature are the Growing Exposure Days (GED) and Growing Degree Days (GDD). The measure GDD is defined as the number of temperature degrees above a base temperature, measured for the crop growing season. The measure GED considers the cumulative number of days of exposures to temperatures within a specified range, the most common being 1^{o}C, 2^{o}C and 3^{o}C intervals. The two measures GDD and GED have been used in several studies such as Tack, Barkley, and Nalley (2015), Lobell et al. (2013), Robertson et al. (2013) and Schlenker and Roberts (2009), all of which used reduced-form statistical models to show that the effect of temperature and precipitation on yield is nonlinear. The advantage of statistical models is that they account for mechanisms that can influence yields in a changing climate such as the plant physiological processes and climate-related influences of pests and pathogens that are not considered in most process-based models (Lobell et al.

2013; Lobell and Field 2006). Also, statistical models can be used to make predictions resulting from temperature increases by using resampling techniques. One limitation of the statistical models is that the predictions do not take into account farmers' responses or the possibility that there could be changes in farm management practices that may reduce the effects of changing climate or weather conditions.

With empirical estimation, the causal effects of weather changes can be estimated if there are no other control variables that are correlated with weather variables to confound the results and if there are no omitted variables. Omitted variables usually arise from unobserved factors that affect the outcome of interest. However, with panel data, fixed effects regression models can be used to control for unobservable location or time-specific characteristics, as well as observable factors. Fixed effects models, therefore, reduce the likelihood of having omitted variable bias arising from unobserved heterogeneity that is assumed to be constant over time (Cameron and Trivedi 2010).

2.3 Data

Plot level data was obtained from the Uganda National Household Survey for the years 2010 to 2015 found in UBOS (2011), UBOS (2012), UBOS (2014), UBOS (2015). For farmers that practice mixed cropping, the proportion of land located to coffee production was estimated as a percentage of the total cropped land size. For example, if a plot of land measuring an acre is intercropped with coffee and bananas, with bananas occupy 40 percent of the land, it implies that the coffee occupies 60 percent of the land, and therefore occupies 0.6 acres. The amount of coffee harvested was estimated based on the weight of the dried coffee beans whereas the yield was estimated by dividing the harvested quantity by the acreage under coffee production. Temperature and precipitation data were obtained from the National Climatic Data Center's (NCDC) Global Surface Summary of the Day archive. The data are comprised of daily precipitation as well as maximum, minimum, and average temperature for the years 2010 to 2014 obtained from 11 weather stations in different parts of Uganda. The weather data was merged with the plot-level data based on the district location. Daily observations of minimum and maximum temperature for each of the 11 weather stations were used to derive the temperature measurements based on the Growing Degree Days (GDDs). The GDDs capture the nonlinear effects of temperature changes on yield as calculated from the difference between an average of minimum, an average of maximum temperature, and a base temperature required for crop growth. The base temperature varies by crop and variety, and was assumed to be 10^{o}C for coffee. The measure is based on the number of days that the plants are exposed to temperatures above the base, and then aggregated the whole for all days in the growing season.

The coffee calendar was used to incorporate the distribution of weather outcomes over the growing season that shows the critical stages of plant growth. Rising (2016) and DaMatta et al. (2007) showed that coffee trees need a spell of water deficit lasting between two to four months to initiate the formation of flower buds and that the dry season should be followed by sufficient rainfall and appropriate humidity to achieve good blossoming. Dry seasons are therefore necessary to initiate flowering and these take place from December to January and also June to July since the country experiences two production seasons in a year. Berry or fruit formation and maturation takes place during the rainy seasons and these take place during February, March, and April for the first production season, and also during August, September, and October for the second production season. For most parts of the country, the harvest seasons start in May and November.

2.4 The Model

The effect of temperature and precipitation changes on yield was modeled based on the biological processes of growing coffee. The critical period of growth was considered as that during which flowering and the fruition takes place (Sachs et al. 2015; DaMatta et al. 2007). Following the approach by Schlenker and Roberts (2009), temperature variables were specified using the growing degree days that are summarized in three temperature ranges or intervals. The regression models were also formulated to include nonlinear effects by including quadratic precipitation variables.

First, a pooled model was formulated as shown in equation (2.1) and estimated by Ordinary Least Squares method. Location and time-specific effects that were assumed to be fixed were included as dummy variables in the regressors X_{it}.

$$\begin{aligned} logy_{it} = \alpha + \gamma_1 prec_{it} + \gamma_2 prec_{it}^2 + \beta_1 Temp_{1t} + \beta_2 Temp_{2t} \\ + \beta_3 Temp_{3t} \\ + prec_{it}(\delta_1 Temp_{1it} + \delta_2 Temp_{2it} + \delta_3 Temp_{3it}) \\ + \sum_{i=1}^{n} \tau_{it} X_{it} + \varepsilon_{it} \end{aligned} \quad (2.1)$$

$logy_{it}$ is the log of coffee yield in the location i at time t, $prec_{it}$ is precipitation, $Temp_{it}$ are the temperature intervals which are: less than 23°C, 23 to 28°C, and greater than 28°C, X_i represents plot characteristics, that include year and location dummy variables. The βs are the coefficients associated with temperature effects that are observed during the growing season, and ε_{it} represents the unobserved factors that affect yield and is assumed to be uncorrelated with other independent variables.

To examine the effects based on temporal variations for weather variables, random effects models were used. With the random-effects model, the effect of temperature extremes was identified by exploiting the variations of temperature and precipitation across locations. A random-effects model was used because the panel of data was very unbalanced. Different plots were observed for each year, making it hard to track the variation of plot characteristics over time. The advantage of the random-effects model is that it yields estimates of all coefficients, including the ones for time-invariant regressors. The regression model in equation (2.1) was reformulated to include time-invariant characteristics c_i as shown in equation (2.2). The underlying assumption with the random-effects model is that the individual-level effects α are uncorrelated with other regressors.

$$\begin{aligned} ly_{it} = \alpha + \beta_1 Temp_{1it} + \beta_2 Temp_{2it} + \beta_3 Temp_{3it} + \gamma_1 prec_{it} \\ + \gamma_2 prec_{it}^2 \\ + prec_{it}(\delta_1 Temp_{1it} + \delta_2 Temp_{2it} + \delta_3 Temp_{3it}) \\ + \sum_{j=1}^{n} \tau_j X_{it} + c_i + \varepsilon_{it} \end{aligned} \tag{2.2}$$

To determine whether the critical temperatures for single-cropped coffee farms differ from the critical temperatures for intercropped farms, equation (2.2) was modified to include interaction variables of temperature intervals with the intensity of intercropping as shown in equation (2.3). $intercrop_{it}$ shows the intensity of intercropping specific for plot i at a time t. The coefficients of interest were the θs that corresponded to interaction variables for temperature and intensity of intercropping. For single cropped coffee plots, the intensity of intercropping $intercrop_{it}$ is equal to zero.

$$
\begin{aligned}
ly_{it} = \alpha + \beta_1 Temp_{1it} + \beta_2 Temp_{2it} + \beta_3 Temp_{3it} + \gamma_1 prec_{it} \\
+ \gamma_2 prec_{it}^2 \\
+ prec_{it}(\delta_1 Temp_{1it} + \delta_2 Temp_{2it} + \delta_3 Temp_{3it}) \\
+ \theta Intercrop_{it} \\
+ Intercrop_{it}(\theta_1 Temp_{1it} + \theta_2 Temp_{2it} \\
+ \theta_3 Temp_{3it}) + \sum_{j=1}^{n} \tau_j X_{it} + c_i + \varepsilon_{it}
\end{aligned}
\tag{2.3}
$$

Because of interaction variables, the marginal effect of weather variables on yield for coffee was estimated by summing up the coefficients of the weather variables as well as the coefficients for the interaction variables multiplied by the mean temperature for the interval. The illustrations for the calculation of marginal effect for precipitation are shown in equation (2.4), where the symbols γ_1 represent the coefficients for precipitation, γ_2 shows the coefficient for precipitation squared, δ_k represents the coefficients for the interaction of temperature and precipitation, and $k = 1,2,3$ represent temperature ranges. $Temp_k$ represents the mean for the temperature range

$$\partial ly_{it} / \partial prec_{it} = \gamma_1 + 2\gamma_2 + \delta_k * Temp_k \quad (2.4)$$

The marginal effects for estimating the effect of increased exposures to the different temperature intervals are as shown in equation (2.5), where β_k represents the coefficient for exposures to different temperature intervals whereas θ_k represent coefficients for interaction variables for temperature and intensity of intercropping.

$$\partial ly_{it} / \partial Temp_{kit} = \beta_k + \delta_k * prec + \theta_k * intercrop \quad (2.5)$$

2.5 Results

2.5.1 Descriptive statistics

A summary of the weather variables, crop and plot characteristics are presented in table 2.1. The results show that the mean of the total precipitation received per season is 17.98 inches with a minimum of 0.06 inches and a maximum of 76.24 inches. The mean temperature for the sample was 22.89^{o}C with an average minimum of 18.02^{o}C and an average maximum of 27.76^{o}C. This is comparable to the mean temperature experienced for the rest of the country, estimated at 22^{o}C (UBOS 2017). The crop characteristics were summarized in the form of yield per acre. The results show a mean yield of dried coffee beans of 666.65 Kilograms (Kg) per acre, with a maximum of 3000Kg and a minimum of 30Kg per acre. Mean yield over the four years shows a steady reduction from 700kg per acre in 2010 to 604 kg per acre in 2014, as shown in appendix B.1. The main factors attributed to yield reduction are pest and diseases and also variations in weather patterns (Jassogne et al. 2014). A simple correlation of yield with average temperature shows that an increase in average temperature during the critical growing period is associated with a reduction in yield. However, a correlation of yield with precipitation shows a weak positive association. The variation in mean yield and the correlation plots are summarized in appendix B.1.

The plot characteristics included the proportion of plots that are intercropped, the topography and the type of soil. The results show that 75.90 percent of the coffee farms were intercropped with bananas. The result is not surprising since Coffee-banana intercropping is widely practiced in Central and Western Uganda. The intensity of intercropping was estimated based on the proportion of the cropped land that is occupied by bananas and coffee. The results showed that the mean intensity was 0.41, with 0.29 standard deviation meaning that on average, 41 percent of the cropped land is occupied by bananas and 59 percent with coffee. For single-cropped coffee farms, the intensity of intercropping is zero, whereas for the intercropped the highest of intensity was limited to 0.9 meaning that 90 percent of the land is occupied by bananas and 10 percent by coffee. The higher the proportion of the cropped land occupied by bananas the higher the intercropping intensity. The landscape of the plot was mostly flat land and gentle slopes and these comprised 35.44 and 47.99 percent of the plots, respectively. Also, the soils were mostly sandy loam and sandy clay loam, comprising of 45.88 and 29.42 percent of the sample. Soil characteristics determine the water holding capacity and therefore clay soils that retain water longer may not be as affected by increasing temperatures or lower rainfall as compared to sandy soils whose water retention capacity is lower (Sachs, 2015).

Table 2.1 Descriptive statistics (n=997)

Weather variables	**Mean**	**SD**	**Minimum**	**Maximum**
Total season precipitation (Inches)	17.98	19.06	0.06	76.24
Minimum Temperature (^{o}C)	18.02	1.77	12.86	21
Maximum Temperature (^{o}C)	27.76	1.21	23.25	30.2
Average Temperature (^{o}C)	22.89	1.22	18.11	24.82
Plot characteristics				
Crop yield per acre (Kilograms)	666.65	671.52	30	3000
Intensity of intercropping (Proportion)	0.41	0.29	0	0.90

	Count	**Percent**
Pure stand	240	24.1
Inter cropped	756	75.9
Topography		
Hilly	97	9.74
Flat	353	35.44
Gentle slope	478	47.99
Steep slope	65	6.53
Valley	3	0.3
Soil type		
Sandy loam	457	45.88
Sandy clay loam	293	29.42
Black clay	191	19.18
Clay loam	37	3.71
Other	18	1.81

2.5.2 Effects of weather variability on yields for coffee

To examine the relationship of weather extremes on coffee yield, different specifications for regression models were employed, and results for the marginal effects are shown in table 2.2. Models 1,2 and 3 were estimated using random-effects regressions. Model 1, was estimated with only weather variables. Model 2 was estimated with weather and control variables that included soil type, topography, region, and year variables. Model 3 was estimated with weather, control variables, and interaction variables between temperature and the intensity of intercropping. For comparison, a pooled model was estimated using Ordinary Least Squares method and the results are presented as model 4 of table 2.2. All model specifications showed consistency in the direction of the coefficients for precipitation and temperature variables. Model 3 estimated using random-effects was the best fit based on the value of the R-squared.

Table 2.2 Marginal effects for regression models

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Precipitation (Inches)	0.0243	0.0268	0.0149	0.0268
	(0.0063)***	(0.0061)***	(0.0047)***	(0.0107)**
Temperature <23 ^{o}C	-0.0001	-0.0003	-0.0001	-0.0003
	(0.0002)	(0.00002)***	(0.0001)	(0.0002)
Temperature 23 to 28 ^{o}C	-0.0005	0.0036	-0.0002	0.0036
	(0.0038)	(0.0002)***	(0.0031)	(0.0046)
Temperature > 28 ^{o}C	-0.0102	-0.0272	-0.0193	-0.0272
	(0.0048)**	(0.0022)***	(0.0117)	(0.0134)**
Control variables				
Proportion intercropped		1.1671	1.1996	1.1671
		(0.1463)***	(0.1755)***	(0.1096)***
Region (base=Central)				

Eastern		0.2790	0.2253	0.2790
		(0.0536)***	(0.0682)***	(0.1296)**
Northern		-0.4274	-0.0585	-0.4274
		(0.3768)	(0.5057)	(0.4253)
Western		0.2021	0.3066	0.2021
		(0.0796)**	(0.0857)***	(0.1287)
Season (base=1st season)				
2nd Season		-0.1531	-0.0253	-0.1531
		(0.1199)	(0.1275)	(0.2096)
Soil type (base=sandy loam)				
Sandy clay loan		0.0844	0.0532	0.0844
		(0.0394)**	0.0513	(0.0767)
Black clay		0.0800	0.0634	0.0800
		(0.1472)	(0.1691)	(0.0832)
Sandy		-0.1847	-0.1908	-0.1847
		(0.0453)***	(0.0741)	(0.1829)
Other		-0.0744	-0.3889	-0.0744
		(0.2545)	(0.2404)	(0.1999)
Topography (base=Hill)				
Flatland		0.0892	0.1306	0.0892
		(0.0856)	(0.0916)	(0.1340)
Gentle slope		-0.0307	0.0230	-0.0307
		(0.1018)	(0.0786)	(0.1282)
Steep slope		0.0863	0.2279	0.0863
		(0.2044)	(0.1505)	(0.1685)
Valley		1.1309	1.0684	1.1309
		(0.3064)	(0.2186)	(0.2519)***
Year (base=2010)				
2011		0.2117	0.1616	0.2117
		(0.0706)***	(0.1024)	(0.1669)
2013		-0.1653	-0.1415	-0.1653
		(0.0384)	(0.0386)	(0.1284)
2014		0.0355	-0.0788	0.0355
		(0.1089)***	(0.0953)	(0.1998)
R^2	0.039	0.1573	0.1616	0.1575

N	997	997	997	997

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

The results showed that an increase in the amount of precipitation during the critical periods had a positive and significant effect on yield. Tack, Barkley, and Nalley (2015), and Schlenker and Roberts (2009) showed that the effect of precipitation can partially mitigate the effect of extreme temperatures. This was tested by including interaction variables between precipitation and the different temperature ranges, and the results are shown in appendix B.2. The results in appendix B.2 showed that the coefficient for temperatures greater than 28 was negative. However, the coefficient for the interaction of temperatures greater than 28^{o}C with precipitation was positive and significant, implying that precipitation mitigates the effect of extreme high temperatures. These results imply that models that do not take into consideration the interactions of temperature with precipitation may not capture the true effect of temperature increases.

The marginal effects of increased days of exposure to different temperature ranges were estimated using a piecewise linear regression based on GDD. The results for the piecewise linear regression are displayed in figure 2.2. The results showed a nonlinear relationship between temperature and yields for coffee, with increased exposure to temperature ranges greater than 28^{o}C and those less than 23^{o}C, resulting in a significant reduction in yield. Temperatures greater than 28^{o}C can inhibit fruit development, encourage early ripening and reduce photosynthetic activity through yellowing and loss of leaves. The marginal effects show that for temperature ranges between 23^{o}C and 28^{o}C, the effect of increasing temperature was positive and significant. The finding that there is a nonlinear relationship between weather variables and yields for coffee are similar to those presented by DaMatta et al. (2007) and Rising (2016) that showed that extremes temperatures beyond 26^{o}C reduced the yields for coffee in Brazil. The same nonlinear relationship has been observed with seasonal crops such as corn (Lobell et al. 2013; Harrison et al. 2011; Lobell and Field 2006) and wheat (Tack, Barkley and Nalley, 2015).

To examine if the effects differ based on the variety of coffee, estimations were made separately for plots with Arabica and Robusta coffee varieties. Given that the data did not include the coffee variety produced, I used district locations to determine the type of coffee variety: Arabica coffee is grown in mountainous areas, and Robust coffee is mainly grown in the Central, Eastern and some parts of Western Uganda.[1] The results based on the variety produced are shown in appendix B.3. The results for Arabica coffee variety show that the effect of both temperature and precipitation was significant. The effect of increases precipitation was positive and the critical temperatures for yield reduction were those greater than 28^{o}C. The optimal temperatures were those between 23^{o}C and 28^{o}C. These results correspond to the findings by Haggar and Schepp (2012), which showed that the optimal temperatures for Arabia coffee in Uganda range between 14^{o}C to 28^{o}C. For Robusta coffee, the effect of increased precipitation was positive and significant but the effect of temperature was not significant.

[1] Districts that produce Arabica coffee include Mbale, Bududa, Sironko, Manafwa, Kisoro and Kibale.

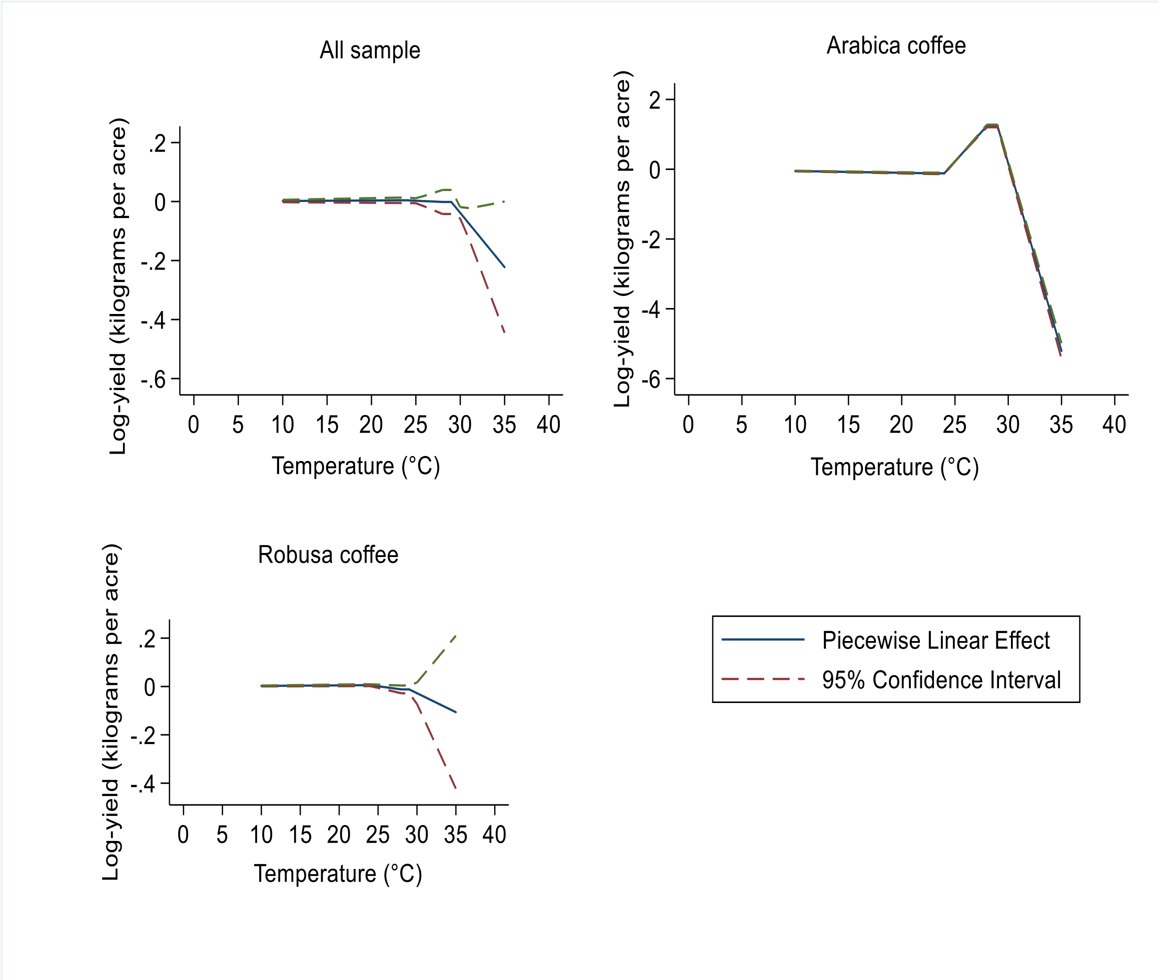

Figure 2.2 Marginal effects for piecewise linear regression by coffee variety

To examine if there are seasonal variations in the effects, the model was estimated separately for season 1 and season 2 and the results for the marginal effects are displayed in appendix B.3. The results show that there are no seasonal differences in the effects of precipitation and temperature on yield. The effects of increased precipitation are positive and the optimal temperatures range between 23^{o}C and 28^{o}C.

To check whether the results are robust to other specifications for temperature variables, the model was estimated based on the Growing Exposure Days (GED) and the results are shown in appendix B.4. The GED measures temperature based on the number of days of exposures to temperatures measured in 5^{o}C temperature bin intervals during the critical growing season and these ranged from 15^{o}C to temperatures greater than 29^{o}C. The results using the GED specification of temperature also showed a nonlinear relationship between the weather variables and yield. The result showed that the critical temperatures for yield reduction were those greater than 30^{o}C. A similar relationship was obtained by DaMatta et al. (2007) who showed that optimal temperatures for the production of Robusta coffee ranges between 20^{o}C to 30^{o}C.

2.5.3 Does intercropping help mitigate the effects of extreme temperature?

To examine whether the effects of extreme temperature differed for intercropped and non-intercropped farms, the model shown in equation (2.2) was estimated and this included interaction terms to show the intensity of intercropping. The results are displayed in appendix B.2 whereas the marginal effects are presented in table 2.2. The coffee plots had different intensities of intercropping ranging between 10 percent and 90 percent where 10 percent intercropped meant that the farm has 90 percent coffee and 10 percent bananas.

The coefficients of interest were the ones corresponding to the interaction of intensity of intercropping with extreme temperatures and these are summarized in appendix B.2. The results for the fixed effects model show that the interaction of temperature above 28^{o}C and intensity of intercropping was negative and significant. These results suggest that an increase in the intensity of intercropping had no significant effect on temperature ranges between 20^{o}C and 28^{o}C, but the effects became significant for increases in exposure to temperature ranges greater than 28^{o}C. Therefore, an increase in the intensity of intercropping partially mitigates the effect of temperature ranges up to 28^{o}C. Also, the results show that an increase in the intensity of intercropping increases the yield per acre. Even though an increase in the proportion of bananas may reduce the overall harvest of coffee per acre intercropped, the calculation of yield is based in the quantity harvested divided by the proportion of land allocated to coffee, and therefore the increase in yield may be realized from the increased harvest per tree. Intercropping with shade plants such as banana plants are used to reduce air temperature, conserve soil moisture, reduce weed growth and reduce soil temperature. (Alemu and Dufera 2017)

The finding provides empirical evidence to suggest the promotion of intercropping as a means to mitigate the effects of extreme heat. Diversification through intercropping also has additional benefits such as increasing the overall value of harvest per acre (Kangire et al. 2011; Asten et al. 2011), reduction of production and marketing risks. Production risks include those arising from weather-induced risks, infestation by pests and diseases whereas market risks arise from

2.5.4 Implications of continued warming

Niang et al. (2014) estimates that by the year 2050, warming in Sub-Saharan Africa will increase by 2^{o}C. The likely effect of increased temperatures on yield was analyzed by assuming uniform increases in temperature of up to 3^{o}C. The models were also estimated to show the likely impacts of warming for all coffee plots that are intercropped with bananas and those that are not and the results are displayed in figure 2.3. These predictions are made under the assumption that no intervention is done to mitigate the effects of warming. The results show that each unit increase in temperature during resulted in a slight reduction in mean yield for plots that are not intercropped but with an increase in mean yield for plots that are intercropped. The results, therefore, show that if no interventions are put in place to mitigate the effects of increasing temperatures, temperature increases will result in reductions in yield for coffee and this will have negative implications for farm and the national income since coffee is the major agricultural export for the country. On the other hand, intercropping with shade plants like bananas can mitigate the effect of increasing temperature and increase mean yield. Intercropping mitigates the effect of extreme heat by shading the coffee plants to reduce water loss through evapotranspiration and also infestation by pests and disease. Also, residues from banana leaves and stem covers are often used as mulch to reduce evapotranspiration and maintain soil fertility.

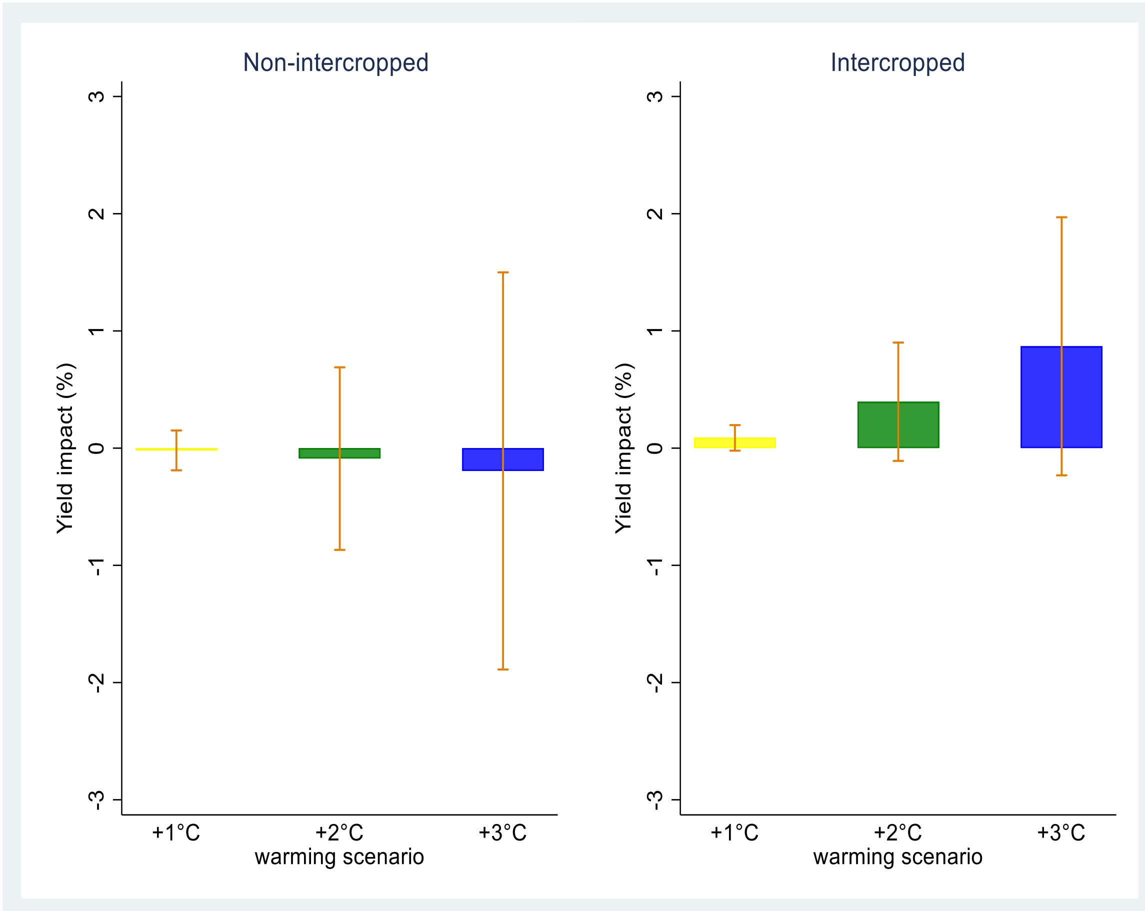

Figure 2.3 Warming impacts assuming with uniform shifts in temperature

The results showed that in an increase in the number of days with exposures to temperatures above the average reduces yield for coffee that is not intercropped, but positive for coffee that is intercropped. However, within the sample, the intensities of intercropping range from 0.1 to 0.9 where the latter implies that 10 percent of the plot is occupied by bananas plants and 90 percent coffee, whereas the latter implies that the plot has 90 percent bananas plants and only 10 percent coffee trees. Bananas are important for food whereas coffee is mainly a cash crop. Therefore, as the intensities of intercropping increase, it means that farmers have to forego coffee trees for more banana plants. There is therefore a tradeoff between increasing food and income and this created the need to derive the optimal intercropping intensity.

To find the optimal intensity of intercropping, the sample was split based on four intervals including: plots with no intercropping, plots with intensities of 0.1 to 0.3, greater than 0.3 to 0.7, and greater than 0.7 to 0.9. The effects of increased temperature were estimated for each of the intervals as shown in figure 2.4. The results of the effect of temperature increases showed a slight reduction in yield for coffee on plots that are not intercropped and a significant increase for plots that are intercropped with an intensity between 0.1 and 0.3. As the intensity of intercropping increased to arrange of 0.3 to 0.7, the yield increase became lower and eventually becomes negative when the intensity is highest between 0.7 and 0.9. These results suggest that the optimal intercropping intensity to guard against yield reduction resulting from increasing temperatures is that between 0.1 and 0.3.

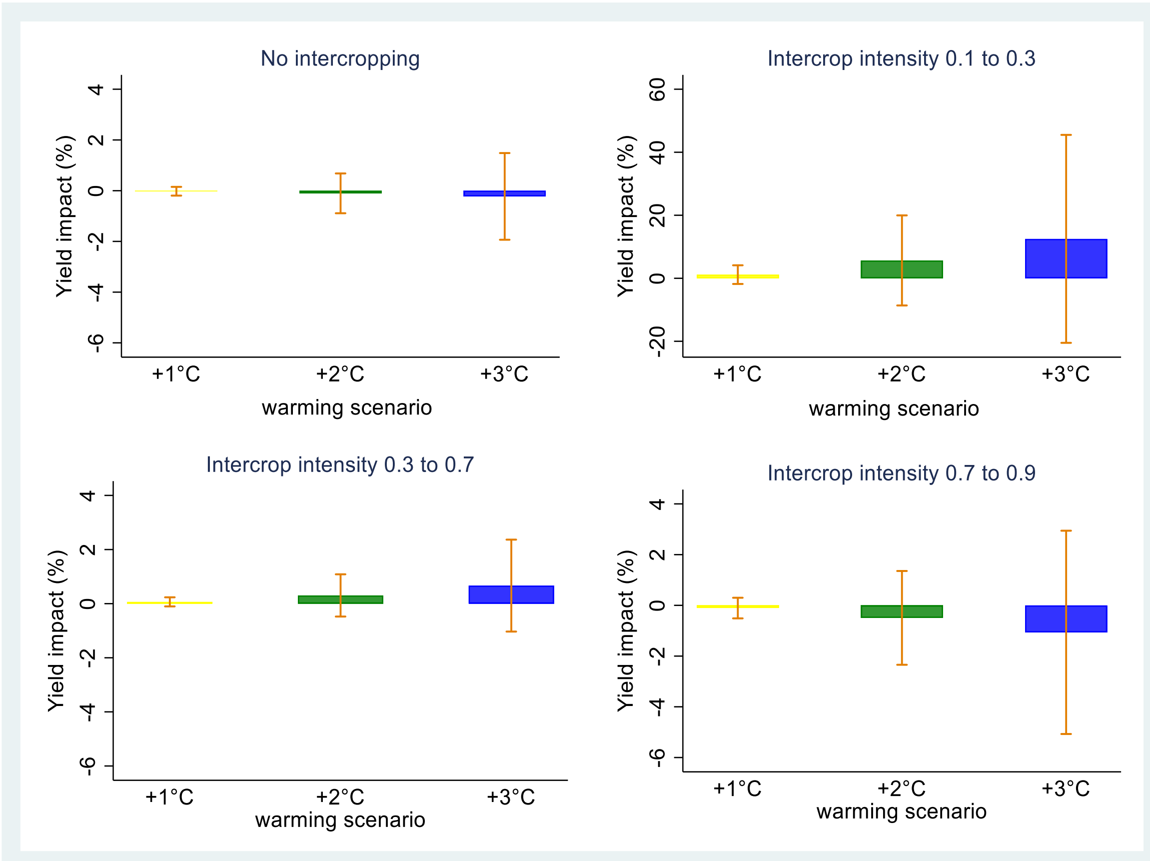

Figure 2.4 Warming impacts based on intensity of intercropping

2.6 Conclusions and Policy implications

The effects of extreme changes in weather on yield for coffee were estimated based on a four-year panel of data. Therefore, the results show the effects of short-term variations of weather on the yields of coffee, implying that more research needs to be conducted to examine the long-term effects. Nevertheless, the results remain useful for informing policies and programs to mitigate the effects of extreme changes in weather. The results show that there is a nonlinear effect of temperature and precipitation on the yields for coffee and that temperature increases will continue to have significant reductions in yield if no action to mitigate the effects. However, the yield reductions are lower for coffee farms that are intercropped with shade crops such as bananas. One limitation of the study is that it did not consider the strategies that farmers are currently using to mitigate the effects of extreme heat other than through intercropping with bananas. However, the majority of the smallholder farmers in Uganda rely on rain-fed agriculture, with less than only one percent using irrigation (UBOS 2010), and less than five percent using improved inputs such as fertilizers. Therefore, having not considered the farmers that irrigate their coffee plots or the inputs used in production does not bias the results.

The significance of the relationship between coffee yield extreme temperatures, precipitation and coffee yield suggests that use of market and non-market based approaches to mitigate the negative effects. Non-market approaches include the adoption of water conservation technologies and intercropping with shade trees and crops whereas market-based approaches include the use of weather index insurance. Weather index insurance can only be promoted in areas that are significantly affected by weather changes. Also, the critical temperatures could be used to design the index and estimate the thresholds for payoffs. However, given the limited understanding of crop insurance within the farming community, this study recommends further to examine the acceptability and socioeconomic effects of using weather index insurance.

In areas that traditionally grow coffee as a single crop, promotion of intercropping with perennial shade trees and crops requires an assessment of the likely tradeoffs over time since it is a long term investment. This study, therefore, recommends for further analysis of the economic viability and perceptions for farming systems that traditionally grow coffee as a single crop. Also, this study recommends more research to be conducted to determine the appropriate level of intercropping that is required to realize significant yield improvements and effective reduction of heat stress using other types of data.

Chapter 3 - Ambiguity Aversion and Preferences for Weather Index-Based Insurance Contracts

3.1 Background

In many developing countries of Sub Saharan Africa, the agricultural sector faces risks and uncertainties resulting from extreme weather fluctuations, which affect farm productivity and the welfare of individuals whose livelihood depends on farming. In response, farmers employ several strategies to mitigate the adverse effects, some of which include income diversification, obtaining credit, sale of assets and mutual support through social networks. However, de Janvry, Dequiedt and Sadoulet (2014), Black et al. (2011), Fafchamps, Udry and Czukas (1998) showed that the use of these strategies does not effectively guard against adverse effects resulting from covariate risks. Covariate risks are shocks that are experienced by all individuals in the community at the same time (Dercon 2011; Barrett 2011). Covariate risks reduce a single individual's ability to support another individual. Examples of covariate risks include weather changes, floods and earthquakes, among others.

One alternative that can be used to overcome adverse effects resulting from covariate risks is the use of index-based insurance. Index-based insurance is an innovative approach to the provision of insurance that compensates for farmers' losses resulting from adverse weather and is based on a predetermined index for loss of assets and investments resulting from weather changes and catastrophic events (Mobarak and Rosenzweig 2013). Several types of index insurance programs have been developed such as yield, livestock, and weather index programs that have been piloted in developing countries of Sub-Saharan Africa in places such as Ethiopia, Kenya, and Malawi. However, these programs have experienced very low levels of adoption and the factors that may affect adoption include cultural beliefs, wealth status, social networks (Ntukamazina et al. 2017; Sibiko, Veettil, and Qaim 2018), high premium prices and basis risk (Jensen and Barrett 2017; Hill et al. 2017; Carter et al. 2014; Jensen, Mude and Barrett 2014; Miranda and Farrin 2012). Basis risk occurs when a farmer incurs a loss but does not qualify for compensation based on predetermined index measurements. Jensen, Mude and Barrett (2014) examined livestock index insurance in Kenya and showed that the proportion of farmers that were insured reduced with each additional year of implementation of the pilot program. Insurance contracts are offered every production season and therefore it is important not only to examine the factors that affect first-time adoption but also continued adoption.

Therefore, this study was conducted to achieve two objectives, the first was to examine the factors that affect adoption and renewal of index insurance contracts and the second objective was to examine farmer preferences for alternatives to weather index insurance and attributes of index insurance contracts. I tested two hypotheses; the first was that ambiguity of the insurance product was significant in affecting adoption and renewal of insurance contracts. Therefore, farmers that are ambiguity averse are less likely to adopt weather index insurance as compared to those that are not. Ambiguity arises from the fact that the predictions about weather conditions and whether the index measurements are correlated with a farmers' loss are not known to the farmer at the time of payment of the premium. It was therefore hypothesized that farmers may opt for other risk management methods whose outcome is known with some level of certainty. Through a choice laboratory experiment conducted in a simulated insurance market, farmers were presented with three alternatives. The first was to purchase insurance as an individual, the second was to purchase through an informal farmers' group and the third was not to purchase insurance at all. The second hypothesis tested was that farmers that choose to purchase insurance have a higher preference for group index insurance contracts as compared to individual insurance contracts. de Janvry, Dequiedt and Sadoulet (2014) showed that small informal groups have a culture of saving and working together to support members when faced with an idiosyncratic shock and therefore the members are more likely to prefer to work together collectively to avoid covariate shocks. The study was conducted in Central and Western Uganda, with a sample comprised of farmers who grow coffee. The focus was on coffee because it is one of the crops that is currently considered by the government for insurance against drought. Also, Wang et al. (2015) show that in Uganda, the adverse effects of extreme weather conditions are greater for Robusta coffee as compared to Arabica coffee.

The use of index and other insurance products is relatively new in Uganda, and the market for insurance is not yet well developed. Therefore, data was collected through a survey and laboratory experiments. The laboratory experiments were conducted in such a way that a hypothetical coffee weather index insurance product for a coffee-growing season was offered to coffee farmers in a simulated insurance market. Coffee farmers made actual monetary payments for premiums and received monetary payoffs at the end of a season, based on the severity of the changes in weather. Farmers were informed of the outcome of each round of the experiment before proceeding to the next. Three experiments were conducted to examine how adoption decisions change over time, with each round representing a different coffee growing season.

To examine the factors that affect the adoption and renewal of insurance contracts, both the cross-sectional logit and dynamic probit models were used. A dynamic probit model was used to control for serial autocorrelation since the outcome from one round of the choice experiment can affect the probability outcome for the next round. The results consistently showed that ambiguity aversion had a negative and significant effect on the adoption and renewal of insurance contracts. To examine farmers' preferences for alternatives and attributes of index insurance contracts, a mixed multinomial logit model was estimated. The results showed that, farmers have a higher preference for group contracts, relative to individual contracts. Also, that basis risk reduces farmers' valuation of index insurance contracts. The results from this study provide evidence that can be used to improve the design of index insurance contracts to suit the preferences of farmers in Uganda. The specific recommendations for consideration in insurance contract design are presented in the last section of this paper. The rest of the paper shows a review of literature on demand for insurance and measurement of risk preferences, a detailed explanation of experiment designs, empirical framework and the results.

3.2 Related studies

Demand and willingness-to-pay for index-based insurance can be examined using stated preference methods, with a limitation that stated preference measures do not necessarily represent the actual behavior of consumers. Since the products are hypothetical, the choices may be different from the actual revealed preferences (Hill et al. 2017; McIntosh, Povell, and Sadoulet 2015). However, in the case where the market for insurance products is not yet well developed or nonexistent, the use of hypothetical products is the only possible choice. A more realistic depiction of consumer behavior can be obtained through a simulated and active market environment in which there are transactions and economic consequences to stating preferences. Simulated markets create incentives for people to critically think about their valuations and investment decisions (Lusk 2003). Sibiko, Veettil, and Qaim (2018), Elabed and Carter (2015); Chantarat, Mude, and Barrett (2009) used stated preference methods and they found that the main factors affecting insurance adoption were related to liquidity, basis risk, low trust in the providers, and poor understanding of the insurance products.

One way of improving the acceptability of index insurance products is to design the contracts based on farmers' needs and preferences. This requires knowledge of the extent of weather variability and the design of insurance contracts based on farmers' endowments and preferences. Some studies have attempted to examine farmer preferences for attributes of insurance contracts such as Castellani (2015) who examined farmers' preference for individual contracts in Ethiopia, and Sibiko, Veettil, and Qaim (2018), who examined farmers' preferences for contracts offered through informal groups in Kenya. In Uganda, the largest percentage of smallholder farmers belong to informal groups through which they share knowledge, mobilize funds for investment and share risks. It is therefore plausible that insurance against covariate risks can also be done through these groups.

Mobarak and Rosenzweig (2013) and Dercon (2011) show that offering insurance through groups enhances learning about the product and also leads to a reduction in transaction costs and basis risk. However, empirical analyses to show farmers' preference for attributes and alternatives for insurance contracts is still limited. This study, therefore, contributes to the limited literature by examining farmers' preferences for attributes for an index insurance contract in a market that offers both individual and group contracts.

Recent literature has attempted to examine the role that risk preferences and attitude play in the adoption of agricultural insurance contracts, whereby risk references are measured using ambiguity aversion. Carter, Elabed and Serfilippi (2016) and Elabed and Carter (2015) show that ambiguity negatively affects the adoption of index insurance. Ambiguity aversion arises when decision-makers choose alternatives with known probabilities over those that have unknown probabilities. Ellsberg (1961) shows that a decision-maker who chooses the alternative with a known probability of a good outcome over one with an unknown probability is said to be ambiguously averse. This can be illustrated by the preference relations $g \succ b$ that shows that a good outcome (g) is strictly preferred to a bad outcome (b). However, the theory shows that a lottery with a both a good and bad outcome with known probabilities (α) and $(1-\alpha)$ respectively, is preferable to a lottery with an unknown probability g'. Therefore, $(\alpha)g + (1-\alpha)b \succcurlyeq g'$. At the time of payment of premium, farmers have little knowledge about the weather condition for the period for which they are insuring and also have no knowledge of whether they will qualify for payoffs in the case of extreme weather changes. Because of the high uncertainty and risk involved, Elabed and Carter (2015) described index insurance as one with compound risk. Farmers may opt to remain without insurance or use other informal insurance methods whose outcome is known with some level of certainty.

3.3 Methods

This section describes the methods used to collect data, design choice experiments, theoretical frameworks used and as well as the results. The analysis and presentation of results is based on the objectives of the study.

3.3.1 Data collection

Data was collected from six sub-counties located in Masaka, Bushenyi and Ishaka districts. Masaka is located in Central Uganda whereas Bushenyi and Ishaka districts are located in Western Uganda. The data was collected by administering a survey as well as conducting choice experiments. The data included demographic characteristics, agricultural production activities, knowledge, as well as the risk management strategies used in production as shown by the sample of the questionnaire in appendix C.1. The area agricultural extension workers were trained and used as research assistants for data collection and conducting the choice experiments. Given that the use of agricultural insurance is new in the study areas, farmers underwent a one-day training to increase their understanding of how the insurance scheme operates and this was done before data collection. The training was comprised of modules about how the insurance scheme is designed, as well as potential benefits and costs. Only the farmers who completed the training were eligible to participate in the choice experiments, and this was made so that the respondents have proper information about how the insurance scheme operates before they make their purchase decision. The sample therefore comprised of farmers who grow Robusta coffee and had completed the training in weather index insurance.

3.3.2 Design of stated choice questions

Given that the largest proportion of the respondents were illiterate and of advanced age, choice questions were designed with three alternatives, two attributes, and two levels. The description of the alternatives and levels are shown in table 3.1.

Table 3.1 Alternatives and attributes for weather index contracts

Alternatives	**Description**
Individual contract	An individual and pay rate specific for individual contracts
Group contract	Obtain insurance as a group and each individual pays an equal premium price based on the premium for the group
No contract	Decision-maker prefers the status quo and has no preference for an individual nor group contract.
Attribute	**Description**
Premium price	The amount required to obtain insurance with 2 levels of hypothetical prices; UgShs2000 and UgShs3000. The prices were randomly assigned to a group or individual contract and these varied for each round of the experiment.
Payment period	The period during which insurance premiums can be paid with two levels; At the start of the production period or during the harvest period for the next production period.

The optimal size of the design was obtained using the formula L^{A*M} where L is the level of attributes, M is the number of alternatives excluding the one for no purchase, and A is the number of attributes. Using PROC OPTEX in SAS version 9.4 (2013), a full factorial of 16 random choices were formulated. The design ensured orthogonality, requiring all attribute levels to be statistically independent of one another and also ensured that each possible pair of attribute levels appears an equal number of times over the design. However too many choice sets can present a cognitive burden to the respondents reducing the response rate and reliability of responses (Hensher, Rose and Green 2015). Therefore, a fractional design with 12 blocks was used to formulate 12 versions of the questionnaire, each with four choice sets that have varying attributes and levels. Each respondent was presented with one version of the questionnaire that had four choice sets each with varying attributes and levels. Respondents were asked to state their most preferred option from the three alternatives. The sample of a choice question used is presented in figure 3.1. To minimize order effects, the sequence of presenting the choice questions was randomized.

Alternatives for a 6-month coffee drought index insurance contract

Attributes	**Alternatives**		
	Individual Contract	**Group contract**	**None**
Premium price (Ug Shs)	2000	3000	
Timing of payment of premium	Start of season	End of season	
Tick only 1 option: I choose to pay for	☐ Option 1	☐ Option 2	☐ Option 3

Figure 3.1 Sample choice question

3.3.3 Design of index insurance laboratory experiment

Choice laboratory experiments to reveal farmers' preferences were designed to reflect an actual scenario for a small-scale coffee farmer producing coffee, with the potential of experiencing a drought and payoffs. The experimental design follows the approach used by Binswanger (2006), where individuals choose among alternatives with varying risk, outcomes and real payoffs are used to induce participants to reveal their preferences. The detailed explanation of the game is presented in appendix C.2. Subjects were presented with the designed choice questions from which they selected their preferred alternative. Subjects who were willing to invest in index insurance paid a fee which was indicated in the insurance contract and that was equated to a premium price to purchase the insurance contract of their choice. The money used to finance premium payments was a proportion of savings from ambiguity aversion games that were played before the start of the experiment. The detailed explanation for the ambiguity game and derivation of ambiguity aversion is presented in appendix C.3.

To represent index insurance against a covariate risk, subjects were divided into groups of ten and for each group a coin flip was used to determine whether the group is eligible for an indemnity payment. If the coin turned out tails, that represents a drought season that triggers an indemnity payment. If the coin turns out heads, that represents a good weather season that does not trigger an indemnity payment. The coin flip also represented the uncertainty regarding whether the changes in weather conditions would trigger an index payment. The insurance game was played three times, with each game representing a coffee-growing season that required a payment of a premium to participate, and a reward with a payoff if the index is triggered.

3.3.4 Theoretical framework

The theoretical framework is based on the assumption of an insurance market that offers both individual and group insurance contracts to farmers. Assume all farmers in a particular location are offered a weather insurance contract at the time t_1 but whose outcome from the purchased is realized in the period t_2. The farmers were presented with an opportunity to insure an acre of coffee. A farmer decides whether or not to purchase the insurance contract. If they decided to purchase insurance, they had an option to purchase individually, or through an informal group to which they belong. Groups are informal because they are not legally registered as entities, but bring together farmers to share knowledge, invest and build social capital.

Consider an informal group of N individuals where each individual $j \in \{1, .. N\}$. Therefore the premium paid by the group is R^g where each individual pays a premium R where $R = R^g/N$. If the insurance premium for an individual, that is not in a group, R^I is greater than R, group members will opt for an individual insurance. It is, therefore, reasonable to assume that the highest price that farmers are willing to pay for insurance while in a group is equivalent to that of an individual and therefore $R^g = R^I = R$.

The factors that affect the decision to adopt are derived from a theoretical framework that builds on the work of Carter et al. (2014) and de Janvry, Dequiedt and Sadoulet (2014). To model insurance decisions, we assume an indirect utility function for an individual j is $U_j = U_j(W_j)$ that is concave, increasing in W. A farmer will buy insurance if:

$$U(W) \leq U(W - R) \tag{3.1}$$

If they purchase the contract, they receive a payoff z when an extreme weather shock occurs at a later time t_2. The payoff (z), depends on whether the weather variable reaches a predefined critical level, or trigger level, and therefore, $z \geq 0$. The willingness to pay for the weather index insurance contract is the amount that makes the group members indifferent between purchasing insurance in the time $t_1$and not purchasing it, as shown in equation (3.2).

$$U\big(W(y_1)\big) - U\big(W(y_1 - R)\big) = \delta Eu\big(W(y_2 + z)\big) - \delta EU\big(W(y_2)\big) \tag{3.2}$$

y_1 and y_2 show the yield outcomes for time-periods 1 and 2 respectively, W_1 and W_1 show the wealth outcomes for the group for periods 1 and 2 respectively, and δ is the discount rate.

The wealth at a time t depends on the yield and the level of consumption smoothing as shown in equation (3.4). Δy_t is the yield shock experienced in period t and β is the consumption smoothing parameter.

$$W(y_t) = W_t^* + \beta(y_t - y_t^*) = W_t^* + \beta(\Delta y_t) \tag{3.3}$$

Following the approach used by Carter et al. (2014), equation (3.3) was substituted into equation (3.2) and a Taylor series expansion conducted. The second-order Taylor series expansion around $W^*$for the left-hand side (LHS) and right-hand side (RHS) of equation (3.2) yields equation (3.4) and (3.5) respectively.

$$\begin{aligned} LHS = \; & U\big(W_t^* + \beta(\Delta y_t)\big) + U'\big(W_t^* + \beta(\Delta y_t)\big) * \beta(\Delta y_t) + \\ & \frac{U''}{2}\big(W_t^* + \beta(\Delta y_t)\big) * \beta^2(\Delta y_t)^2 - U\big(W_t^* + \beta(\Delta y - R_t)\big) - U'(W_t^* + \beta(\Delta y_t) - R) \\ & * \beta(\Delta y_t - R) - \frac{U''}{2}(W_t^* + \beta(\Delta y_t) - R) * \beta^2(\Delta y_t - R)^2 \end{aligned} \tag{3.4}$$

$$\begin{aligned} RHS = \; & U\big(W(y_2 + z)\big) + U'\big(W(y_2 + z)\big) * \beta\delta EZ + \frac{U''}{2!}\beta^2\big(W(y_2 + z)\big) * \delta EZ \\ & - U\big(W(y_2)\big) - \beta U'\big(W(y_2)\big) - \frac{U''}{2!}\beta^2\big(W(y_2)\big) \end{aligned}$$

$$\delta EZ - \frac{U''}{2!}\delta\beta^2\left(E(z+\Delta y_2)^2 - \left(E(\Delta y_2)\right)^2\right)$$

$$\delta EZ - \frac{U''}{2!}\delta\beta^2\left(E(z)^2 + 2E(Z\Delta Y_2)\right) \tag{3.5}$$

The factors that affect the decision to purchase insurance are obtained by equating equations (3.4) to (3.5) and this yields equation (3.6). The detailed derivation is shown in appendix C.4.

$$R(1-\beta\Delta y_1\rho) + \frac{1}{2}\beta R^2\rho - \delta EZ - \frac{1}{2}\rho\delta\beta^2\left(E(z)^2 + 2E(Z\Delta Y_2)\right) = 0 \tag{3.6}$$

The coefficient of risk aversion is ρ, and is obtained by $\rho = -\frac{U'^*}{U''^*}$ where $U'^*$and U''^* are the first and second derivatives of the utility function U^* at W^*. From equation (3.6), it can be concluded that the decision to invest in index insurance depends on the premium (R), consumption smoothing parameter (β), ambiguity aversion (ρ), and a discount rate (δ). Also, the correlation between the yield shock (Δy_2) and the payout (Z) determines whether the farmer incurs basis risk that also affects the decision to invest in weather index insurance.

3.3.5 Empirical framework

Consumer preferences elicited through contingent valuation methods are modeled based on random utility theory (Hensher, Rose and Green 2015). The random utility theory assumes that a decision-maker n obtains utility from choosing alternative j is given by $U_{njt} = V_{njt} + \varepsilon_{njt}$ where V_{njt} is a function of observable attributes of the alternatives

X_{njt}, and of the decision-maker Z_{nt} and ε_{njt} is an error term. The probability that the decision-maker n chooses an alternative j is

$$\begin{aligned} P_{njt} &= Pr\left(U_{njt} > U_{nit}\right) \forall\, j \neq i \\ &= Pr\left(V_{njt} + \varepsilon_{njt} > V_{nit} + \varepsilon_{nit}\right) \forall\, j \neq i \\ &= Pr\left(\varepsilon_{nit} - \varepsilon_{njt} < V_{njt} - V_{nit}\right) \forall\, j \neq i \end{aligned} \quad (3.7)$$

Different types of discrete models can be formulated based on the assumptions about the distribution of the random terms. For this study, three types of discrete choice models were formulated and these included the logit model, bivariate probit model and the mixed multinomial logit model.

i. Logit model

Factors affecting adoption of index insurance was analyzed using a logit model framework with the dependent variable (Y_i) taking on a value of 1 if a premium payment for insurance was made and 0 otherwise. The dependent variables included respondent characteristics X_n and location variables Loc_n. The time-invariant characteristics of an individual n include literacy level (Lit_n), age (Age_n), sex (sex_n), ambiguity aversion (AA_n) whereas the time-variant characteristics included the savings that a respondent has at the start of each round of the choice experiment ($save_{nt}$). Respondent characteristics are invariant because they did not change across the different rounds of the choice experiments. Location variables were included to capture unobserved differences in cultural practices, weather conditions, and demographics across the different locations. The logit model is summarized in equation (3.8) where $F(z) = e^z/1 + e^z$ is the cumulative logistic distribution. The model was then estimated using Maximum Likelihood.

$$Prob(Y_{nj} = 1) = F(\gamma_1 AA_n + \gamma_2 X_n + \gamma_3 Loc_{nj} + \gamma_4 save + \varepsilon_{nt}) \tag{3.8}$$

ii. Dynamic probit model

The factors that affect the likelihood that an individual would renew their insurance contract was examined using a dynamic probit model. A dynamic probit model takes into account the correlation between the binary dependent variable y_{it} and the unobserved heterogeneity u_{it} affecting y_{it}. The equation for the latent dependent variable for the dynamic probit model is specified as shown in equation 3.9 and it includes the lagged dependent variable as a covariate.

$$y_{it}^* = \gamma y_{it-1} + \beta Z_{it} + c_i + u_{it} \tag{3.9}$$

The variable y_{it}^* is the latent dependent variable and it expresses the likelihood that an individual will ensure whereas y_{it} is the observed binary outcome variable. The subscripts i and t index individuals and time-periods respectively, where $i = 1, \dots., N$ and $t = 1,2,3$. Z_{it} is a vector of time-varying explanatory variables that are strictly exogenous, c_i which is the unit-specific unobserved effect, and u_{it} is the idiosyncratic error term that is assumed to be serially independent. The transition probability for individual i at time t, given c_i is given by equation (3.10) where $\Phi = (.)$ is the distribution function of the standard normal distribution.

$$Pr\left(y_{it} \middle| Z_{it}, y_{it-1,} c_i\right) = \Phi(\gamma y_{it-1} + \beta Z_{it} + c_i) \tag{3.10}$$

Following Rabe-Hesketh and Skrondal (2013), the unit-specific unobserved effect c_i can be written as shown in equation 3.11 where y_{i0} and Z_{i0} represent the initial value of the response variable and of the time-varying explanatory variables respectively. $\bar{Z}_l = \frac{1}{T}\sum_{i=0}^{T} Z_{it}$ stands for the within unit averages of the explanatory variables where averages are based on all time-periods $t = 0, \dots, T$. α_i is a unit-specific time-constant error term, normally distributed with mean 0 and variance σ_a^2.

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{Z}_l + \alpha_3 Z_{i0} + \alpha_i \tag{3.11}$$

Unobserved heterogeneity is addressed by including in the model the initial period value of the dependent variable and the initial period unit averages of time-varying explanatory variables. Since unobserved heterogeneity is captured by c_i, the $t - 1$ lagged value of the response variable can be interpreted as state dependence which is the causal effect exerted by the use of insurance in one period, on its use in the subsequent period.

$$\begin{aligned} Pr\left(y_{it} \middle| Z_{it}, y_{it-1,} c_i\right) &= \Phi(\gamma y_{it-1} + \beta Z_{it} + c_i) \\ &= \Phi(\gamma y_{it-1} + \beta Z_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{Z}_l + \alpha_3 Z_{i0} + \alpha_i) \end{aligned} \tag{3.12}$$

The individual time-invariant characteristic of the individuals included their age, sex, location, a dummy variable showing whether an individual is ambiguity-averse. The time-varying characteristic of the individual was the amount of cash savings that they had at a specific time (X_{it}) and these were calculated from the payoffs less premiums paid in the previous round of the choice experiment. The savings for the previous period (X_{it-1}) were also included as additional covariates. Estimation of the dynamic probit model was based on the marginal maximum likelihood random parameters approach which requires to formulate a distribution for the parameters α_i so that

$$p(y_i|\alpha_i, X_i, y_{i0}) = \prod_t p\left(y_{it}\middle|\alpha_i, X_{it}, y_{i,t-1}\right) \tag{3.13}$$

A STATA software package developed by Grotti and Cutuli (2018) was used to estimate the effects and post estimation commands used to estimate the steady-state expected dynamics for significant time-invariant covariates.

iii. Mixed logit model

Respondents were provided with choice sets that had alternatives for insurance contracts that included an individual contract, a group contract and an option to purchase any. To examine farmers' preferences for the alternatives and attributes for the insurance contracts, a mixed multinomial logit was used. The mixed logit model was used because it relaxes the assumption that observations are Independent and Identically Distributed (IID). Correlation among observations is common with choice experiments and could lead to inefficiency of the estimates (Hensher, Rose and Green, 2015). The Mixed logit model also makes it possible to account for heterogeneity in preferences which are unrelated to observable characteristics and is specified in equation (3.14).

$$Prob\left(choice_{nt} = j\middle|X_{njt}, Z_n, V_n\right) = \frac{exp\left(V_{njt}\right)}{\sum_{j=1}^{J_{ns}} exp\left(V_{njt}\right)} \tag{3.14}$$

$V_{njt} = \beta_n' X_{njt}$ and $\beta_n = \beta + \Delta z_n + \tau V_n$. X_{njt} are the k attributes of alternative j in the choice situation faced by individual n at a time t, z_n is a set of characteristics of individual n that influence the mean of taste parameters and V_n a vector of k random variables with zero means and known variances and zero covariance. The indirect utility function that shows the independent effect of each attribute level upon the response variable choice is presented in equation (3.15).

$$V_{nj} = \beta_{0j} + \beta_{1j} f(X_{1j}) + \beta_{2j} f(X_{2j}) + \gamma_1 Lit_n + \gamma_2 Age_n + \gamma_3 sex_n + \gamma_4 AA_n + \gamma_5 payoff_{nt} + \varepsilon_{nt} \tag{3.15}$$

Where β_{0j} is the constant specific for alternative j, β_{ij} is the weight associated with attribute X for and alternative j. The time-invariant characteristics of an individual n include literacy level (Lit_n), age (Age_n), sex (sex_n), ambiguity aversion (AA_n) whereas the time-variant characteristic was a dummy variable showing whether or not the individual received a payoff $(payoff_{nt})$. The model assumption is that the effect of each attribute is independent of all other attributes and therefore the values for the coefficients can be used to estimate the WTP for a k attribute as shown in equation (3.16).

$$E(WTP^k) = -\frac{E(\beta^k)}{E(\beta^{pre})} \tag{3.16}$$

Identification requires sufficient variability in the independent variables. However, with the repeated panels, the individual and location characteristics are fixed, since they do not change for games conducted within the same period. Therefore, random effects were used to exploit the heterogeneity in individual preferences across different locations. Also, the efficiency of parameters was ensured by obtaining a large sample size with a sufficient number of observations. One of the problems that may undermine the reliability and stability of the estimates for inference is that the choice tasks comprised of labeled alternatives have the potential to bias respondents. However, given that insurance contracts had never been used before in the study areas, bias was not a problem since the farmers had no prior experience of using either contract. Given that the objective of this study was to examine the relative preference for alternatives and attributes, the use of labeled alternatives was relevant to estimate alternative specific constants. Also, labeled alternatives add realism to the experiment and can also make up for omitted attributes (Hensher, Rose and Green 2015).

3.4 Results and discussion

3.4.1 Respondent and product characteristics

The choice experiments involved administering two treatments. The first treatment was offered in Western Uganda, where all farmers were presented with an individual insurance contract, with fixed attributes that included a premium price of 2000 Uganda Shillings per acre of coffee and for premium payments to be done at the start of the production season. However, the farmers in Central Uganda were presented with the second treatment which was a flexible insurance contract with options to pay premiums individually or through a group. The proportion of farmers that took up insurance was higher with the flexible contracts as compared to the fixed contracts as shown in table 3.2.

The descriptive statistics show a high demand for index-based insurance in the Central region, with 93.5 percent of the respondents purchasing at least one time. Out of these, 59.4 percent opted for group contracts whereas 34.21 percent opted for individual contracts and 6.45 percent had no preference for any contract. The respondents that did not purchase an insurance contract preferred the status quo that included using other risk management strategies or no having no risk reduction strategy at all. The average premium payments were 2500 Shillings, although this was a hypothetical amount specific to the game. The actual premium rate on the market for Uganda is 25,000 Shillings per acre after including the subsidy provided by the government. Also, 48.63 percent of the respondents preferred to purchase insurance during the start of the production period. The results also showed that the percentage of male respondents and those that were ambiguity averse as well as the mean number of years was higher for the central region as compared to the Western region. However, the percentage of respondents with very low levels of education was higher in the Western region as compared to the Central region as shown in table 3.2.

Table 3.2 Summary statistics (n=291)

Characteristics	**Description**	**Central region (n=182)**	**Western region (n=109)**
Premium rate	Mean premium rate	2500	2000
	Minimum premium rate	2000	2000
	Maximum premium rate	3000	2000
	Standard Deviation	50.01	0
Age of respondents	Mean number of years	49.82	40.65
	Minimum age	22	21
	Maximum age	80	76

	Standard Deviation	13.24	12.00
Savings(USD)	Mean savings	1108.38	22000
	Minimum savings	-5000	0
	Maximum savings	28000	1197.31
Contract option	Individual contract (%)	34.21	37.92
	Group contract (%)	59.34	
	No contract (%)	6.45	62.08
Payment period	Preference for start of season (%)	48.63	100
	Preference for end of season (%)	44.87	0
Ambiguity aversion	Percentage ambiguity averse (%)	72.53	33.95
Sex (percentage male)	Percentage for male (%)	68.13	40.75
Education	Low with primary level and less	58.89	70.64
	Moderate with secondary school level	29.12	23.85
	Highly educated beyond secondary level	10.99	5.51

3.4.2 Factors affecting adoption of weather index insurance

The factors that affect the adoption of insurance were examined using a mixed-effects logit regression that controls for both fixed and random effects. The marginal effects are presented in table 3.3 with model 1 showing the results for the whole sample, whereas the model 2 and 3 show results for Western and Central regions respectively.

The results for the whole sample show that holding other factors constant, farmers who are ambiguity averse are 5.16 percent less likely to invest in index insurance as compared to those who are not and this result was significant at the five percent level. In the Western region, farmers who are ambiguity averse are 14.12 percent less likely to adopt index insurance as compared to those who are not and the result was significant at five percent level. The results also suggest that ambiguity is location-specific since the coefficient was significant for the Western region but not the Central region. A possible explanation for the difference in ambiguity for the two regions is that the Central region is more exposed to risks resulting from weather changes and disease infestations and therefore the farmers in this region have more experience undertaking risky investments as compared to those in the West.

The education of the respondents was significant in influencing the adoption of insurance for the whole sample and the Central region. The results showed that farmers in the Central region that have post-secondary education are 5.87 percent times more likely to adopt insurance compared to those with primary education whereas those with post-secondary education are 9.34 percent more likely to adopt. The results for the Central region show that education increases the likelihood of adopting insurance. Education increases access to knowledge that increases one's ability to take on risks and to understand the value of the product. For the Western region, farmers with post-secondary education are less likely to adopt insurance as compared to those that have primary education or less. This is because the highly educated farmers in Western Uganda, have additional off-farm income that can be used to make up for losses resulting from weather changes. The farmers in the Central region have higher levels of education but are involved in farming as the main source of income with less involvement in off-farm employment.

Farmers' savings were measured based on the amount that they had accumulated before the start of the insurance games. The summary statistics in table 3.1 showed that the farmers in the Western region have lower savings as compared to those in the central. However, the effect of savings on the adoption of insurance was not significant for the

Western region but was negative and significant for the Central region. An increase in farmers' savings reduces the likelihood of adopting index insurance by 19.01 percent. This is because savings are an alternative form of self-insurance and therefore can be a substitute for the formal insurance.

Other factors that were significant in influencing the adoption of insurance in the Central region were the age and sex of the respondents. The results showed that an increase in age by one year increases the likelihood of adopting insurance by 0.52 percent. However, the effect of age on adoption was nonlinear as shown by the coefficient of the quadratic age variable that was negative. Older farmers have a higher ability to process information. The results show gender differences in the adoption of insurance where male farmers are 3.40 percent more likely to adopt insurance as compared to the females. The result is not surprising since the societies are patriarchal where women are less involved in decision making and the men have control over resource use and investments.

Table 3.3 Marginal effects for factors affecting adoption of weather index insurance

Independent variables	Whole sample	Western region	Central region
	Model 1	**Model 2**	**Model 3**
Individual characteristics			
Age in completed years	0.0052	-0.0049	0.0119
	(0.0048)	(0.0129)	(0.0036)***
Sex of respondent (Female=0; Male=1)	-0.0056	-0.0218	0.0340
	(0.0216)	(0.0562)	(0.0189)*
Ambiguity aversion	-0.0516	-0.1412	0.0006
	(0.0238)**	(0.0621)**	(0.0203)
Savings in USD equivalent	-0.0589	0.2301	-0.1901
	(0.0661)	(0.1858)	(0.0592)***
Education (base= primary level or lower)			
Secondary level	0.0587	0.0983	0.0587

	(0.0244)**	(0.0679)	(0.0186)***
Post-secondary education	0.0577	-0.1824	0.0934
	(0.0334)*	(0.0968)*	(0.0172)***
Location dummies			
Kabonera	0.7893		
	(0.0485)***		
Kyabugimbi	0.2685	0.2315	
	(0.0664)***	(0.0689)***	
Kyanamukaaka	0.7253		-0.0542
	(0.0482)***		(0.0340)
Mukungwe	0.7975		0.0158
	(0.0449)***		(0.0291)
Nyakabirizi	0.2631	0.2364	
	(0.0795)***	(0.0824)***	
Ruhumuro	0.2727	0.2694	
	(0.0675)***	(0.0771)***	
N	1,052	324	728
Log pseudo likelihood	-368.4406	-198.5974	-153.5713
Wald chi-squared	301.33	28.02	60.42
Probability > chi2	0.0000	0.0018	0.0000

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

3.4.3 Factors affecting the likelihood that farmers would renew insurance contracts

Equations (3.12) was estimated using maximum likelihood with the dependent variable being whether or not a farmer renewed their insurance contract. The marginal effects on the likelihood of renewing insurance contracts are summarized in table 3.4. The results showed that ambiguity aversion was a limitation to continued use of index insurance. Respondents who were ambiguity averse were less likely to take up index insurance compared to those who were not and this was by 59.65 percent. Similar findings were obtained by Bryan (2019) and Slingerland (2017), who showed that ambiguity aversion significantly reduced the likelihood of adoption of index insurance in Mali and Kenya respectively. This result suggests the need to reduce the ambiguity of insurance contracts if a higher uptake is to be achieved.

The results also showed that the purchase of insurance in the previous season increases the likelihood of purchasing insurance for the next season as shown by the positive coefficient. Farmers that purchase insurance are more likely to appreciate the benefits of index insurance and this induces them to purchase renew their insurance contracts.

The location of the respondents also influences the likelihood of renewing insurance contracts. The coefficients for locations in Central Uganda were all positive and significant and these included Mukungwe, Kabonera and Kyanamukaaka. This implies that farmers in Central Uganda are more likely to purchase insurance as compared to those in the Western region. This could be because the study locations in the central region is being affected by unpredictable weather changes as compared to those in the Western region. It is important to note that the data was an instantaneous panel, therefore not much variation over time in the characteristics of the respondents. This could be the reason why the variables that did not change between the rounds of the game were not significant.

Table 3.4 Marginal effects for factors affecting renewal of insurance contracts

Variables	**Marginal effects**
Individual characteristics	
Age in completed years	-0.0014
	(0.0083)
Sex of respondent (Dummy, 1 if male)	0.0336
	(0.1973)

Ambiguity aversion (Dummy, 1 if averse)	-0.5965
	(0.25557)**
Education level (Base= Primary level)	
Secondary level	0.0149
	(0.2167)
Post-Secondary level	0.3697
	(0.4320)
Savings (USD)	-0.0004
	(0.0011)
Initial conditions	
Lag dependent variable (1 if insured)	3.0517
	(0.5921)***
Initial insurance condition	-0.5738
	(0.6180)
Initial savings	-0.0005
	(0.0009)
Average savings	0.0007
	(0.0017)
Locations	
Kabonera	2.2992
	(0.5521)***
Kyabugimbi	-0.5729
	(0.3760)
Kyanamukaaka	1.6702
	(0.4092)***
Mukungwe	2.1952
	(0.4107)***
Nyakabirizi	-0.5384
	(0.4393)
Ruhumuro	0.0936
	(0.3948)
Constant	-1.8230
	(0.5460)***
N	580
Wald chi-square	183.82
Log-likelihood	-125.7391
p-value	0.000

***, **, * Significance at 1%, 5%, 10% level.

Based on the model estimates, predicted patterns of the dependent variable were derived and summarized in table 3.5. The predicted probabilities show the likely outcome at a period t for a farmer that purchased insurance in the previous period $t-1$. The outcomes at time t included; the probability of not renewing the contract conditional on having purchased the contract in the previous period $Pr(0|1)$, the probability of renewing the insurance contract, conditional on having purchased insurance in the previous period $Pr(1|1)$. Also, the probability of purchasing insurance at a time t given that the farmer did not purchase in the previous period $Pr(1|0)$, was obtained. The results showed that the probability that a farmer will renew their insurance contract was significant at 0.05 percent level and was estimated at 0.93, implying that farmers that purchase insurance in one period have a higher likelihood of purchasing insurance in the next period. The probability that a farmer would not renew their insurance contract was not significant and was estimated at 0.07. The likelihood that a farmer who did not purchase insurance in the previous period would purchase in the current period was low, estimated at 0.0680.

Table 3.5 Transitional probabilities for renewing insurance contracts

Outcomes for a previous insured farmer	Probability	Standard error
Probability of not renewing the contract $Pr(0\|1)$	0.0655	0.06373
Probability of renewing the contract $Pr(1\|1)$	0.9320	(0.0215)**

** Significant at 5%

3.4.4 Preferences for attributes of index insurance contracts

A mixed multinomial logit model was used to examine preferences for index insurance attributes with one alternative dropped to avoid collinearity and the option dropped was not to buy any type of insurance. The software used for both models was the Nlogit version 5, and mixed multinomial logit model results are obtained with 1000 Halton draws. The results show the mean marginal utilities and mean standard deviations that were estimated through simulated maximum likelihood. The marginal utilities show the relative preference orderings for the attributes whereas the standard deviations show how wide preferences are distributed throughout the population.

A Random Parameter Logit Model (RPLM) was estimated and this included Alternative Specific Constants (ASCs), insurance contract attributes and the decision-makers' characteristics. The statistical significance of the contract attributes and respondent characteristics was tested using the Wald statistic and the associated probability-values. The results showed that the Alternative Specific Constants (ASCs) for the two insurance contracts were both positive and significant, indicating that on average, other factors not included in the model positively affect the choices for alternatives. However, the constant for the group contract was twice as large as that for the individual contract implying that the effect of unobserved factors is higher for group contracts as compared to the individual contracts.

The results also show that on average, there is a statistically significant disutility associated with basis risk. A similar result was found by (Ward, Spielman, and Ortega 2015) who used choice experiments to examine preferences for attributes for bundled insurance products. Basis risk reduces farmers' incentive for investment in index insurance when farmers' losses are not correlated with the index measurement. The individual characteristics that were significant in affecting utility for index insurance was the literacy level of the respondents whereby literate farmers are more likely to value insurance contracts as compared to the illiterate farmers.

The results show that the attributes for premium price and timing of payment were not significant. It was therefore not possible to determine the willingness to pay for the attributes. Nevertheless, the results can be used to show the relative preference for the alternatives for insurance contracts. Following the Lancaster theory (1966), I assume that utility derived from the consumption of the complete bundle of insurance contracts is simply as an additive function of the part-worth utilities for the individual attributes. Under this assumption a summation of part-worth utilities shows that on average, the utility derived from using group contracts is higher than that from individual contracts.

To check the robustness of the results, other model specifications were used that included the conditional logit model and the Error Components Model (ECM) and the results are summarized in Table 3.5. The results were consistent with those obtained when the random parameters model was used and they all show a higher preference for group contracts arising from unobserved attributes and a disutility associated with basis risk. The results showed that the random parameters logit model had the best fit because it had value for the Log-likelihood function that was closest to zero and the least value for the Akaike Information Criteria.

Table 3.6 Results for part-worth utilities

Variables	**RPLM**	**RPLM**	**CL**	**ECM**
Alternative Specific Constants				
Individual contract	2.04346 (0.5717)***	4.1228 (1.5174)***	2.0891 (0.7147)***	3.9688 (1.4418)***

Group contract	3.7742 (0.6309)***	5.5132 (1.5414)***	2.5785 (0.7118)***	5.3458 (1.4896)***
Contract attributes				
Premium (USD)	-0.6037 (0.6121)	-0.8287 (0.7410)	-0.1031 (0.4367)	-0.8128 (0.7389)
Payment period	0.1854 (0.1664)	0.3244 (0.2046)	0.1287 (0.1237)	0.3208 (0.2041)
Individual characteristics				
Ambiguity aversion		-0.1295 (0.3647)	0.0130 (0.1718)	-0.0695 (0.3567)
Sex		0.2659 (0.3546)	0.0509 (0.1637)	0.2335 (0.2335)
Age		0.0020 (0.0273)	0.0867 (0.0131)	0.0036 (0.0258)
Literacy (1 if post-primary education)		0.6529 (0.3569)*	0.3137 (0.1724)*	0.4990 (0.3465)
Payoff (1 if payoff was not received)		-2.2224 (0.2727)***	-1.2996 (0.1160)***	-2.1739 (0.2619)***
Locations				
Mpugwe		-0.1583 (0.5609)	-0.0153 (0.2907)	-0.2485 (0.6104)
Kabonera		-0.9735 (0.5640)*	-0.5723 (0.2891)***	-1.0647 (06104)*
Likelihood function	-470.7949	-791.0009	-497.3870	-384.8135
Akaike Information Criterion	953.6	792.4	1016.8	795.6
Chi-square	640.4120	815.6163	248.2532	812.3746
Probability value	0.0000	0.0000	0.0000	0.0000
Pseudo R squared	0.4048	0.5156		0.5135
Number of observations	720	720	720	720

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

3.5 Summary, conclusion and policy implications

The objective of the study was to examine the factors that affect the adoption and renewal of index insurance contracts. Consistent with the findings from other studies, our results show a negative effect of ambiguity aversion on the likelihood of adoption of index insurance. The second objective was to examine the preferences for alternatives and attributes of index insurance contracts. Following the Lancaster (1966) theory, the results show a higher preference for group contracts compared to individual contracts. The results also show that not receiving a payoff for a previous insurance contract, reduces the utility or value of using index insurance. Whether or not farmers value insurance contracts is important because it determines the farmers' revealed preference for the contracts. The findings, therefore, have important implications for the design of the contracts. The first is that providers of index insurance products should consider the heterogeneity in farmer characteristics, risk exposure and risk preferences and therefore design contracts to suit their specific resources, needs and characteristics. The second implication is that insurance contracts that compensate for both weather-induced and other kinds of losses are likely to be more valued as compared to those that compensate based on the weather index only. When farmers incur losses, the payoffs received as compensation are an incentive for famers to invest in insurance for the subsequent period.

The results from the choice experiment suggest that offering contracts through farmer groups could be a viable way of increasing insurance uptake. Group contracts have the additional benefits of reducing transaction costs, basis risk and also being important platforms for information exchange. The study, therefore, suggests that rather than promote and pilot one type of contract, promoters of weather index insurance should pilot the two types of contracts and invest in research to improve the efficiency of the two designs. The third implication is that there should be continued provision of information for both the group and individual contracts, to reduce their ambiguity. Information should constantly be provided about the execution of the contract, likely changes in weather conditions and possible effects on productivity. This would reduce the uncertainty associated with the insurance contracts and therefore encourage uptake. It is important to note that even though the respondents for this research were coffee farmers in Uganda, the recommendations suggested are applicable for the design of weather index insurance for different crops and are also applicable to for improvement in the design of index insurance contracts in other developing countries. The study, therefore, contributes to the literature on weather index insurance by focusing on the behavioral and product-specific factors that affect farmers' valuation of insurance contracts.

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Appendix A - Supplementary material for Chapter 1

A.1 Results for Principle Component Analysis

Factor analysis/correlation

Table A1. Factor Analysis

Factor	Eigenvalue	Proportion	Cumulative
Factor 1	2.4236	0.2424	0.2424
Factor 2	1.4845	0.1484	0.3908
Factor 3	1.0217	0.1022	0.4930
Factor 4	0.9494	0.0949	0.5879
Factor 5	0.8411	0.0841	0.6720
Factor 6	0.8066	0.0807	0.7527
Factor 7	0.6914	0.0691	0.828
Factor 8	0.6509	0.0651	0.8869
Factor 9	0.6120	0.0612	0.9481
Factor 10	0.5188	0.0519	1.0000

LR test: independent vs. saturated: chi2(45) = 3203.46 Prob>chi2 = 0.0000

Prediction of the wealth index was based on the coefficients for different assets

Table A.2 Scoring coefficients based on regression estimates

Variable	Factor 1	Factor 2	Factor 3
Furniture	0.1731	0.3107	0.1553
Appliances	0.2498	-0.2701	-0.030
Television	0.2681	-0.2991	-0.0261
Radio	0.2349	0.3200	0.0199
Bicycle	0.0819	0.4725	-0.2716
Motorcycle	0.1512	0.0313	-0.0616
Vehicle	0.1713	-0.2500	0.1231
Jewelry	0.2287	-0.0634	-0.0471
Mobile phone	0.2850	0.1042	-0.0765
Other assets	0.0281	0.1034	0.9230

Average inter-item covariance: 0.0193728

Number of items in the scale: 10

Scale reliability coefficient: 0.6086

A.2 Marginal effects based on wealth status

Table A.3 Marginal effects based on wealth status

(Dependent variable Y = Whether or not a worker migrated)		
Variables	Low wealth	High wealth
Precipitation (Inches)	0.0404	0.0287
	(0.0077)***	(0.0060)***
Temperatures <24^{o}C	0.0023	0.0016
	(0.0003)***	(0.0003)***
Temperatures 24 to 29^{o}C	-0.0219	-0.0144
	(0.0032)***	(0.0028)***
Temperatures >29^{o}C	0.0707	0.0468
	(0.0094)***	(0.0082)***
Weather shock (Base=No shock)	0.0244	-0.0273
	0.0417	0.0341
Age (Complete years)	-0.0034	0.0000
	(0.0014)**	0.0012
Sex (Base=Female)	-0.0021	-0.0063
	0.0310	0.0267
Marital status (Base=Not married)	0.0158	0.0359
	0.0342	0.0335
Education level (Base=Primary level)		
Ordinary level	-0.0472	0.0773
	0.0416	(0.0327)**
High school level	0.0925	-0.1119
	0.2597	(0.0672)*
Tertiary and higher	-0.0947	0.0695
	0.1182	0.0555
Farmer (base =Off-farm employment)	-0.0388	0.0709
	0.0442	0.0540
Household size	-0.0042	-0.0003
	0.0056	0.0040
Sample size	677	1176
Wald chi-squared	77.5900	81.7400
Probability value	0.0000	0.0000
Pseudo R-squared	0.1299	0.0648
Log pseudo likelihood	-316.9249	-647.4291

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

Appendix B - Supplementary material for Chapter 2

B.1 Graphs for summary statistics

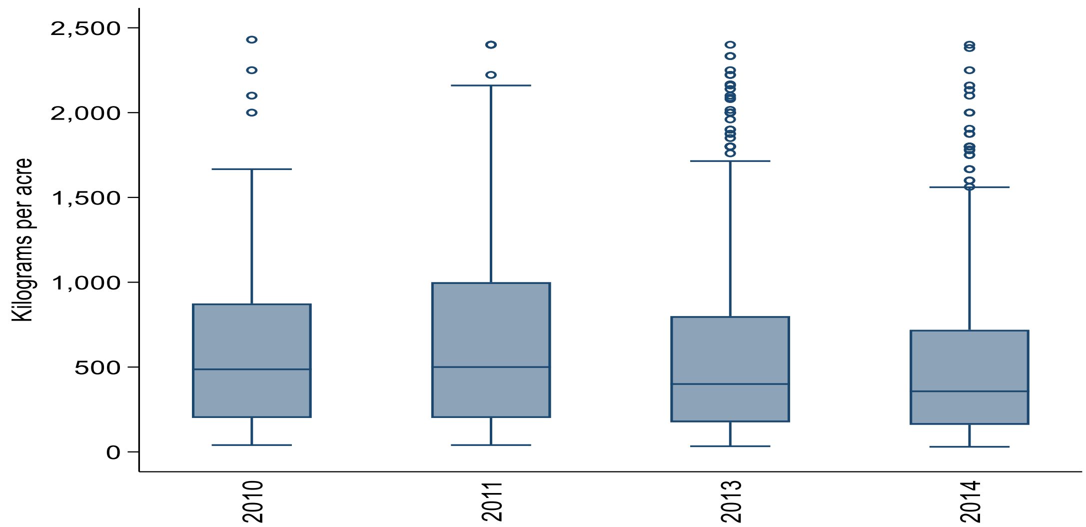

Figure B.1: Variation of yields over the years

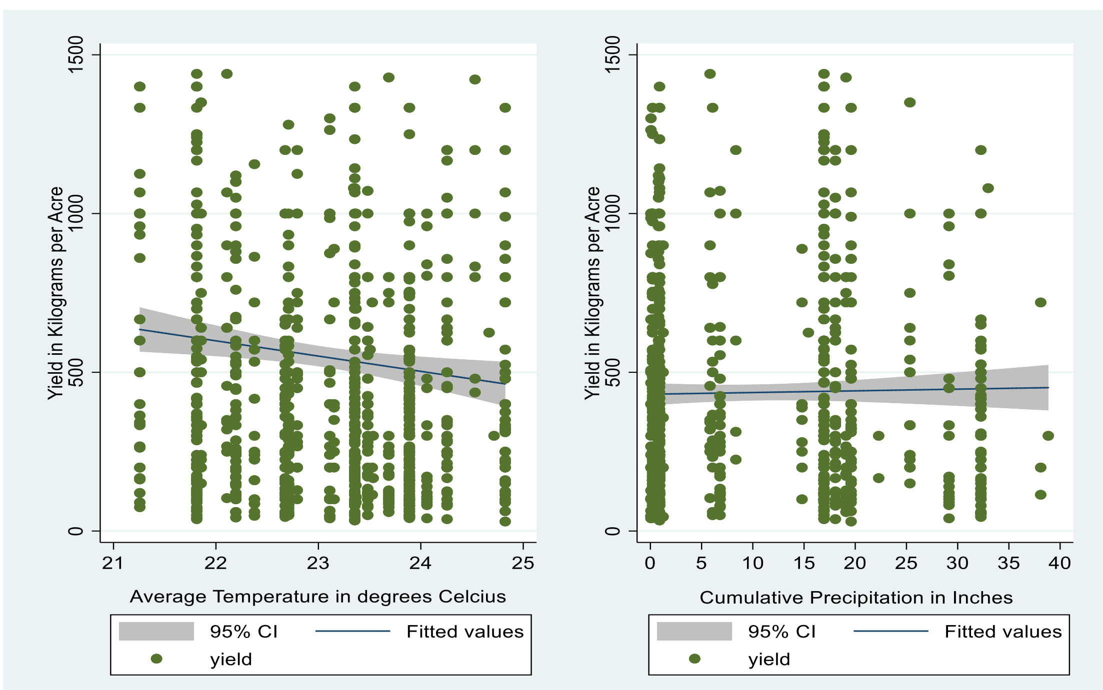

Figure B.2 Correlation of yield with average temperature and precipitation

B.2 Regression results

Table B.1 Results for random effects and OLS regressions

Variables	**Model 1**	**Model 2**	**Model 3**
Precipitation (Inches)	0.017	0.0176	0.0176
	(0.0052)***	(0.0055)***	(0.0157)
Precipitation squared (Inches)	0.0008	0.0009	0.0009
	(0.0004)**	(0.0004)**	(0.0006)
Temperature <23 °C	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)
Temperature 23 to 28 °C	0.0006	-0.0013	-0.0014
	(0.0026)	(0.0042)	(0.0059)
Temperature > 28 °C	-0.0432	-0.037	-0.0368
	(0.0053)***	(0.0073)***	(0.0220)*
Precipitation # Temperature <23 °C	-0.00002	-0.000008	-0.00008
	(0.00001)*	(0.00001)*	(0.0002)
Precipitation # Temperature 23 to 28 °C	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0003)
Precipitation # Temperature > 28 °C	0.0009	0.0009	0.0009
	(0.0002)***	(0.0002)***	(0.0007)
Proportion intercropped # Temperature <23		-0.0001	-0.0001
		(0.0001)	(0.0002)
Proportion intercropped # Temperature 23 to 28 °C		0.0041	0.0042
		(0.0032)	(0.0049)
Proportion intercropped # Temperature > 28 °C		-0.0184	-0.0187
		(0.0066)***	(0.0178)
Proportion intercropped	1.1626	1.0991	1.1086
	(0.1386)***	(0.1989)***	(0.1558)***
Region (base=Central)			
Eastern	0.2771	0.3103	0.3123
	(0.0487)***	(0.0385)***	(0.1326)**
Northern	-0.429	-0.4399	-0.4416
	(0.3862)	(0.3639)	-0.4385
Western	0.1999	0.1952	0.1976
	(0.0716)***	(0.0740)***	-0.1292

Season (base=1st season)			
2nd Season	-0.1688	-0.1689	-0.154
	(0.1324)	(0.1376)	(0.2114)
Soil type (base=sandy loam)			
Sandy clay loan	0.0874	0.0786	0.0758
	(0.0386)**	(0.0377)**	(0.0769)
Black clay	0.0749	0.0692	0.0744
	(0.1396)	(0.1403)	(0.0835)
Sandy	-0.1857	-0.1988	-0.1983
	(0.0433)***	(0.0527)***	(0.1839)
Other	-0.0703	-0.1029	-0.1066
	(0.2465)	(0.2284)	(0.2029)
Topography (base=Hill)			
Flatland	0.0879	0.092	0.0936
	(0.0833)	(0.0883)	(0.1343)
Gentle slope	-0.0276	-0.0263	-0.0292
	(0.0990)	(0.1022)	(0.1285)
Steep slope	0.0882	0.0902	0.0885
	(0.1965)	(0.2014)	(0.1693)
Valley	1.1346	1.1368	1.1336
	(0.2916)***	(0.3076)***	(0.2628)***
Year (base=2010)			
2011	0.2122	0.2159	0.2158
	(0.0649)***	(0.0635)***	(0.1673)
2013	-0.1671	-0.1737	-0.1717
	(0.0362)***	(0.0367)***	(0.1289)
2014	0.0503	0.0476	0.0337
	(0.1253)	(0.1231)	(0.2015)
Constant	5.4109	5.443	5.4386
	(0.1301)***	(0.1651)***	(0.1831)***
R^2	0.1563	0.1575	0.1586
N	997	997	997

Model 1: Random effects model with temperature and precipitation interaction variables

Model 2: Random effects model with temperature and precipitation interaction variables, and interaction variables for temperature and intensity of intercropping.

Model 3: OLS model with temperature and precipitation interaction variables, and interaction variables for temperature and intensity of intercropping.

B.2 Marginal effects for alternative model specifications

Table B.2 Marginal effects for alternative model specifications

Dependent variable = Log yield	Based on coffee varieties		Based on production seasons	
Variables	**Arabica coffee**	**Robusta coffee**	**Season 1**	**Season 2**
Precipitation (Inches)	-0.6998	0.0279	0.0282	0.1218
	(0.0470)***	(0.0061)***	(0.0056)***	(0.1013)
Temperature 20 to 24 ^{o}C	0.0056	-0.0003	-0.0004	-0.0022
	(0.0004)***	(0.00001)***	(0.0001)***	(0.0006)***
Temperature 25 to 29 ^{o}C	0.2063	0.0034	0.0068	0.0405
	(0.0029)***	(0.0005)***	(0.0030)**	(0.0265)
Temperature > 29 ^{o}C	-0.9475	-0.0277	-0.0339	-0.1482
	(0.0089)***	(0.00090***	(0.0094)***	(0.0236)***
Control variables				
Proportion intercropped	1.1180	1.1651	1.2590	0.9849
	(0.4159)***	(0.1569)***	(0.1408)***	(0.0568)***
Region (base=Central)				
Eastern		0.3123	0.2775	0.2056
		(0.0429)***	(0.1040)***	(0.0499)
Northern		-0.4416	-0.6734	
		(0.3395)	(0.5307)	
Western		0.1976	0.2085	0.9118
		(0.0823)**	(0.1375)	(0.2858)***
Soil type (base=sandy loam)				
Sandy clay loam	0.2501	0.0758	0.1275	0.0602
	0.0292	(0.0382)**	(0.0533)**	(0.0276)**
Black clay	0.3876	0.0744	0.1518	-0.0687
	(0.0678)	(0.1479)	(0.1995)	(0.0249)***
Sandy		-0.1983	-0.1757	
		(0.0547)***	(0.0779)**	

Other	0.7146	-0.1066	-0.0775	-0.0246
	(0.1335)	(0.2284)	(0.0930)	(0.3186)
Topography (base=Hill)				
Flat land	0.2501	0.0758	0.1185	0.0756
	0.0292	(0.0382)**	(0.1118)	(0.0322)**
Gentle slope	0.3876	0.0744	0.0589	-0.1180
	(0.0678)	(0.1479)	(0.0767)	(0.0324)***
Steep slope		-0.1983	0.2485	-0.2829
		(0.0547)***	(0.1277)*	(0.0200)***
Valley	0.7146	-0.1066	1.4942	0.6751
	(0.1335)	(0.2284)	(0.2188)***	(0.0264)***
Year (base=2010)				
2011		0.2158	0.1876	0.4883
		(0.0698)***	(0.0910)**	(0.2103)**
2013		-0.1717	-0.1789	-0.1383
		(0.0393)***	(0.0357)***	(0.1286)
2014		0.0337		0.1768
		(0.1103)		(0.1669)
Season (Base=season 1)	-0.5428	-0.1540		
	(0.1739)***	(0.1303)		
R^2	0.2609	0.1602	0.2042	0.0874
N	183	814	658	337

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

B.3 Marginal effects based on growing exposure days

Table B.3 Marginal effects based on exposure days

Variables	**Model 1**	**Model 2**	**Model 3**
Precipitation (Inches)	0.0410	0.0268	0.0358
	(0.0093)***	(0.0069)***	(0.0150)**
Temperature 15 to 15 ^{o}C	-0.0150	-0.0259	-0.0174
	(0.0148)	(0.0062)***	(0.0187)
Temperature 20 to 24 ^{o}C	0.0723	0.0250	0.0358
	(0.0238)***	(0.0121)**	(0.0270)
Temperature 25 to 29 ^{o}C	-0.0964	-0.0296	-0.0503
	(0.0263)***	(0.0134)**	(0.0345)
Temperature > 29 ^{o}C	-0.0502	-0.0369	-0.0662
	(0.0114)***	(0.0077)***	(0.0075)***
Control variables			
Proportion intercropped		-0.0369	1.1628
		(0.0077)***	(0.1412)***
Region (base=Central)			
Eastern		0.1421	0.2414
		(0.0579)**	(0.0439)***
Northern		0.1136	0.2120
		(0.2385)	(0.4136)***
Western		0.2309	0.2714
		(0.1086)**	(0.0825)
Soil type (base=sandy loam)			
Sandy clay loan		0.0781	0.0900
		(0.0365)**	(0.0375)**
Black clay		0.0697	0.0845
		(0.1603)	(0.1490)
Sandy		-0.2550	-0.1609
		(0.0687)***	(0.0413)***
Other		-0.1342	-0.0854
		(0.2939)	(0.2596)
Topography (base=Hill)			
Flatland		0.1309	0.0520
		(0.0712)*	(0.0667)
Gentle slope		0.0293	-0.0733
		(0.0971)	(0.0811)
Steep slope		0.1398	0.0582
		(0.1901)	(0.1856)

Valley		1.1776	1.0455
		(0.3154)***	(0.2566)***
Year (base=2010)			
2011		0.2624	0.2856
		(0.0417)***	(0.0539)
2013		-0.1719	-0.0931
		(0.0338)	(0.0275)
2014		-0.0104	0.0756
		(0.0865)	(0.1126)
season		-0.1599	-0.1314
		(0.0882)*	(0.1299)
R-squared	0.0428	0.1489	0.1594
N	997	997	997

***, **, * Significance at 1%, 5%, 10% level. Standard errors in parenthesis

Model 1: Regression with only weather variables

Model 2: Regression with weather and control variables.

Model 3: Regression with weather variables, control variables and variables for interactions for temperature and intensity of intercropping.

Appendix C - Supplementary material for Chapter 3

C.1 Questionnaire and sample choice set

SECTION 1: General Information

Questionnaire number [ ]

For the responses below, fill in the blank spaces

1.1	Date of interview ……………………………………..	1.5 Village ………………………………………………..
1.2	District …………………………………….	1.6 Name of respondent (Optional) ……………………...
1.3	Sub-county …………………………………….	1.7 Mobile number of respondent ………………………
1.4	Parish …………………………………….	1.8 GPS Coordinates for the household …………………

SECTION 2: Respondent characteristics

2.1 Sex of the respondent ………………………………………….

2.2 Age: ………………………….. years

2.3 Education level a. None b. Primary c. Secondary d. Tertiary

2.4 What is your main religion? ……………………………………………………………

2.5 How long have you been growing coffee? ………………………………………………

SECTION 3: Production characteristics

3.1 In which year was the coffee planted? ………………………………………………………

3.2 What is the size of the plot that you use for coffee production? ………………………………

3.3 What crops do you intercrop with coffee? …………………………………………………

3.4 What percentage of the plot is allocated to coffee? …………………………………………

3.5 What is the main type of soil that is found on the plot that you use for coffee production?

a. Loam soil b. Sandy soil c. Clay soil

3.6 How would you best describe the topography of the land on which coffee is produced?

a. Flatland b. Slope c. Valley

SECTION 4: Risks and adaptation strategies

4.1 What are the common types of risks that you face in coffee production? Please rank them and state the nature of loss that you incurred over the past year

Risks in production	**Rank**	**Frequency in the past 6 months**	**How much was lost? (Quantify)**
Excessive rainfall			
Low rainfall			
Excessive heat			
Floods			
Pests/Diseases			
Thefts of produce			
Others, specify …………………			

4.3 What strategies do you use to mitigate water scarcity resulting from low rainfall or increasing temperatures? ……………………………………………………………………………..

5.0 AGRO-Insurance

5.1 Have you heard of any agricultural insurance products being sold over the past year?

Yes/No……………………………………

5.2 If yes, from what sources did you hear about the agricultural insurance product?..

5.3 Did any member of your household purchase the agricultural insurance product? Yes/No

…………………………………………

If No, please state the 2 most important reasons why you did not take up the insurance?

……………………………………………………………………………………………….

………………………………………………………………………………………………

5.4 If you took up the agricultural insurance,

How many times have you been able to insure?	Month and year	What type of insurance did you purchase?	How much did you pay as premium for each of the times?	How many acreages for coffee did you insure?	Did you receive a discount that reduced the premium price of insurance?	What was the percentage reduction in the premium price of insurance?
1st time						
2nd time						

3rd time						

5.5 If purchased once, what is the reason for this?

………………………………………………………………………………………

5.6 Have you ever received any kind of indemnity payment for a loss that you incurred?

Yes/No…………………………………….

5.7 What loss did you incur that triggered it? (Quantify the loss)

………………………………………………………………………

5.8 How much did you receive as compensation?

…………………………………………………………………………………

5.9 How many times have you purchased agricultural insurance, suffered a loss but did not receive compensation? …….…………

5.10 How many times have you purchased agricultural insurance, never suffered loss but received compensation? …………………….

5.11 If you have not yet taken up agricultural insurance, would you be willing to take it up in the future? Please respond to this question by considering the choice sets presented to you.

Choice set Question

If you have not yet taken up agricultural insurance, would you be willing to take it up in the future? Please respond by considering the choice sets presented to you. Consider the options below as possible choices sets for insurance contracts. In the last row, please choose the option with the combination of attributes (profiles) that best matches your preferences

BLOCK 1

Choice sets for attributes of an index Insurance contract

Set 1

Sequential games for a 6-month coffee drought index insurance contract

Attributes	Individual Contract	Group contract	None
Premium price	2000	3000	
Timing of payment of premium	Start of season	Start of season	
I choose to pay for	☐ Option 1	☐ Option 2	☐ Option 3

Set 2

Sequential games for a 6-month coffee drought index insurance contract

Attributes	Individual Contract	Group contract	None
Premium price	2000	3000	
Timing of payment of premium	Start of season	Harvest time	
I choose to pay for	☐ Option 1	☐ Option 2	☐ Option 3

Set 3

Sequential games for a 6-month coffee drought index insurance contract

Attributes	Individual Contract	Group contract	None
Premium price	2000	3000	
Timing of payment of premium	Harvest time	Harvest time	
I choose to pay for	☐ Option 1	☐ Option 2	☐ Option 3

Set 4

Sequential games for a 6-month coffee drought index insurance contract

Attributes	Individual Contract	Group contract	None
Premium price	3000	3000	
Timing of payment of premium	Harvest time	Start of season	
I choose to pay for	☐ Option 1	☐ Option 2	☐ Option 3

C.2 Explanation of insurance game

The concept for the choice experiment was based on the assumption that the main objective of the farmer is to maximize profits by growing coffee (Y) that is sold at a price P_y , with production costs C. The yield distribution has a mean *E(Y)* and a variance *var(Y)*. If the farmer purchases weather index insurance, they pay a premium Pre. Farmers have the option to purchase an individual insurance contract or a group contract. With a group contract, a group premium is set that is then divided equally among the group members. For simplicity I show that the premium and payoffs do not differ for the two types of contracts.

If the farmer purchases an insurance contract and has a valid index and a good yield, the payoff will be $\pi_I = P_y Y - C - Pre + I$. In case a farmer with insurance experiences a bad season and incurs a loss in yield L, the payoff is $\pi_I = P_y Y - C - Pre - L + I$ where I is an indemnity that is based on the predicted index measurement and is not correlated with the farmers' loss. If the index is valid, $I > 0$ and if invalid, $I = 0$.

$$I = \begin{cases} (L_a - T_a) * Acres_i * P_y \\ \quad 0\ otherwise \end{cases} \tag{8}$$

where L_a is the predicted crop failure based on the index for an area a and T_a is the trigger level for an area a, Acres is the total number of acres insured by the farmer *i* and P_y is the price of coffee. If a farmer purchases an insurance contract, has a bad yield with an invalid index, the payoff is $\pi_I = P_y Y - C - Pre - L$. If the farmer does not buy insurance, there is no premium payment and no indemnity, so the payoff is $\pi_{NI} = P_y Y - C - L$ if they incur a bad yield and $\pi_{NI} = P_y Y - C$ if the yield is good. The possible outcomes for the farmer are summarized in figure 1, adapted from Elabed and Carter

(2015). The decisions at each stage are sequential, and therefore farmers make choices regarding the use of index insurance with an unknown probability of what the outcome would be. Farmers, therefore, choose between using index insurance with an ambiguous probability of the outcomes, as compared to not insuring or using other forms of risk management whose outcomes are known with a certain level of certainty.

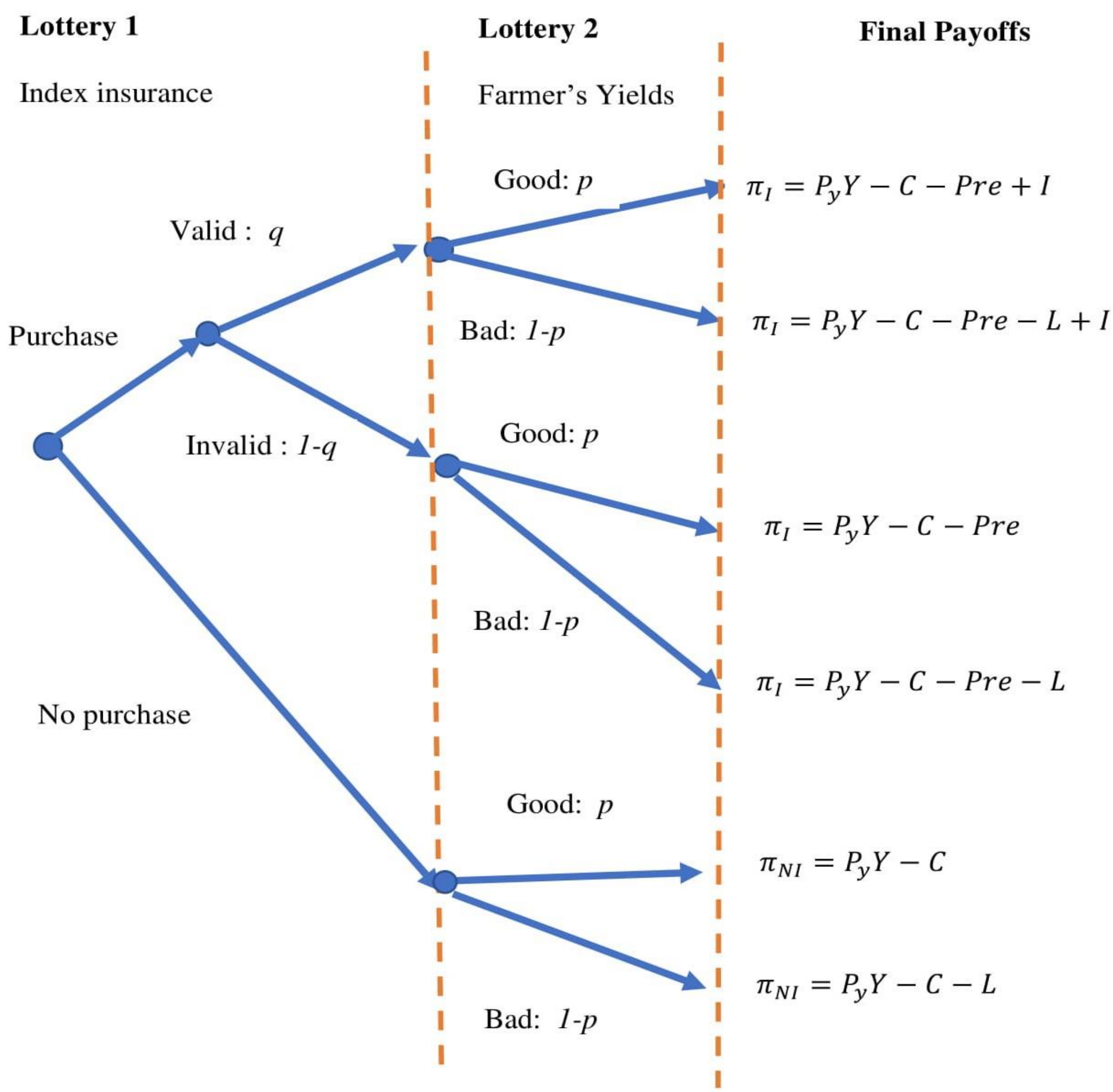

Figure C.1. Illustration of sequences and payoffs for insurance game

C.3 Explanation for the Ambiguity game

The approach used for the ambiguity game follows that used by Dimmock and Kouwenberg (2013) and Slingerland (2017). Subjects were presented with three glasses containing both red and white beads totaling to 100. Each glass has a different proportion of red balls at 30%. 50% and 70% for games 1,2, and 3 respectively. An opaque cup was also presented that contains 100 beads but with an unknown proportion of red and white beads. For each round of the game, one transparent glass and an opaque glass where presented to the respondents to randomly pick a bead from their preferred glass. The game was played 3 times with each round having a different proportion of red and white beads for the transparent glass.

Each white bead that was randomly selected yielded a payoff whereas a red bead yielded no payoff. Therefore, the total savings that a farmer had were equivalent to the payoffs from three rounds of the game. ambiguity aversion game. A framer was considered ambiguity averse if they selected the transparent glass at least 2 times from the three rounds the game was played.

I choose (tick option)
- ☐ Option 1
- ☐ Option 2
- ☐ Indifferent

Option **1**: 30% red , 70% white Option **2**: Unknown proportion

I choose (tick option)
- ☐ Option 1
- ☐ Option 2
- ☐ Indifferent

Option **2**: 50% red , 50% white Option **2**: Unknown proportion

I choose (tick option)
- ☐ Option 1
- ☐ Option 2
- ☐ Indifferent

Option **3**: 70% red , 30% white Option **2**: Unknown proportion

*The number of beads are symbolic of the contents for the glass. Each cup contained 100 beads

Figure C.2. Choice sets for ambiguity game

C.4 Derivation of factors influencing uptake of index insurance

$$U\big(W(y_1)\big) - U\big(W(y_1 - R)\big) = \delta Eu\big(W(y_2 + z)\big) - \delta EU\big(W(y_2)\big)$$

$$LHS = U\big(W(y_1)\big) - U\big(W(y_1 - R)\big)$$

$$LHS = U\big(W_t^* + \beta(\Delta y_t)\big) + U'\big(W_t^* + \beta(\Delta y_t)\big) * \beta(\Delta y_t) + \frac{U''}{2}\big(W_t^* + \beta(\Delta y_t)\big) * \beta^2(\Delta y_t)^2 - U\big(W_t^* + \beta(\Delta y - R_t)\big) - U'(W_t^* + \beta(\Delta y_t) - R) * \beta(\Delta y_t - R) - \frac{U''}{2}(W_t^* + \beta(\Delta y_t) - R) * \beta^2(\Delta y_t - R)^2$$

$$LHS = (-R) + U'\big(W_t^* + \beta(\Delta y_t)\big) - \beta(\Delta y_t - R) + \frac{U''}{2!}(-R) * \beta^2(\Delta y_t - R)^2$$

$$LHS = U(-R) + -\beta(\Delta y_t)\,(-R)\,U'(*) + (-R)\beta^2 \Delta y_t \frac{U''(*)}{2!}$$

$$RHS = \delta Eu\big(W(y_2 + z)\big) - \delta EU\big(W(y_2)\big)$$
$$= \delta Eu\big(W(y_2)\big) + \delta Eu\big(W(z)\big) + \delta Eu\big(W(y_2)\big)$$

$$U\big(W(y_2 + z)\big) + U'\big(W(y_2 + z)\big) * \beta\delta EZ + \frac{U''}{2!}\beta^2\big(W(y_2 + z)\big) * \delta EZ - U\big(W(y_2)\big) - \beta U'\big(W(y_2)\big) - \frac{U''}{2!}\beta^2\big(W(y_2)\big)$$

$$\delta EZ - \frac{U''}{2!}\delta\beta^2\left(E(z + \Delta y_2)^2 - \big(E(\Delta y_2)\big)^2\right)$$

$$\delta EZ - \frac{U''}{2!}\delta\beta^2\big(E(z)^2 + 2E(Z\Delta Y_2)\big)$$

Equating LHS = RHS

$$(-R) + -\beta(\Delta y_t)\,(-R)\,U'(*) + (-R)\beta^2\Delta y_t \frac{U''(*)}{2!} = \delta EZ - \frac{U''(*)}{2!}\delta\beta^2\big(E(z)^2 + 2E(Z\Delta Y_2)\big)$$

$$-R - \beta(\Delta y_t)\,(-R)\,U'(*) + (-R)\beta^2\Delta y_t \frac{U''(*)}{2!} - \delta EZ - \frac{U''(*)}{2!}\delta\beta^2\big(E(z)^2 + 2E(Z\Delta Y_2)\big) = 0$$

But $\rho = -\frac{U'(*)}{U''(*)}$

$$-R - \beta(\Delta y_t)\,(-R)\,\rho + \,(-R)\beta^2 \Delta y_t \frac{\rho}{2!} - \,\delta EZ - \,\frac{\rho}{2!}\delta\beta^2\big(E(z)^2 + 2E(Z\Delta Y_2)\big) = \,0$$

$$R(1 - \beta\Delta y_1\rho) + \frac{1}{2}\,\beta R^2\rho - \,\delta EZ - \,\frac{1}{2}\rho\delta\beta^2\big(E(z)^2 + 2E(Z\Delta Y_2)\big) = \,0$$