Measuring Farmers' Risk and Uncertainty Attitudes: An interval Prospect Experiment

Toritseju Begho

Thesis Submitted in Partial Fulfilment of the Requirement for the Degree of Doctor of Philosophy

Department of Applied Economics, Marketing and Development
School of Agriculture, Policy and Development

September 2018

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Toritseju Begho

September 2018

Abstract

Attitudes to risk have generated a lot of attention over the years due to its vital importance in decision-making processes that are necessary for life and livelihoods. Attitudes towards uncertainty have received less attention even though arguably most important decisions are under uncertainty rather than risk. In addition, many studies modelling attitudes to risk have adopted experiments that place significant cognitive burden on respondents. Crucially, they are also framed in a way that do not reflect everyday problems. Specifically, the most common way of eliciting attitudes is to ask decision makers to choose between discrete monetary lotteries with known probabilities attached to the payoffs. Yet, arguably, the vast majority of choices that people make in their day-to-day lives are with respect to continuous non-monetary outcomes. To address these gaps, this thesis investigates responses to continuous 'prospects' across different conditions (risk & uncertainty), contexts (monetary & time) and content domains (gain, loss & mixed). Further, this thesis examines the link between attitudes to risk/uncertainty and mental health related factors and the effect of attitudes to risk and uncertainty on farmers' decisions both for themselves and for others.

This thesis uses both non-parametric methods - relating to the patterns that characterise participants' choices and their determinants; and parametric models – based upon cumulative prospect theory (CPT) as it extends to continuous prospects. The data were gathered using lab-in-field experiments in which Nigerian farmer's chose between pairs of prospects with continuous distributions, which were not exclusively monetary in nature. Attitudes towards risk, as opposed to uncertainty were elicited by specifying that all outcomes over the specified interval were 'equally likely' (thus a uniform probability density). Uncertainty was specified by indicating to farmers that one outcome within the specified interval would be realised but without the specification of an associated probability density.

Key findings are that attitudes differ under different conditions, contexts and content domains. Using continuous prospects, respondents did not treat equally likely outcomes as 'equally likely' and appear to demonstrate cumulative probability distribution warping consistent with the CPT. However, there were behaviours that are difficult to reconcile with CPT such as the preferences of many respondents could only be modelled using "extreme curvature" of the value function. This was induced by what we term *negligible gain avoidance* (*i.e.* avoiding prospects with zero lower bound in the gain domain) or *negligible loss seeking* (*i.e.* preferring prospects with zero upper bound in the loss domain) behaviours. CPT, Salience theory, Heuristics and other theories examined in this study could not alone explain these behaviours. Results from investigating the effect of bipolar disorder tendencies (BD) on risk attitudes show that BD significantly affects the shape of the value and probability weighting functions; and farmers that have BD are more likely to make random choices. Other results show that risk aversion for losses increases participation in off-farm income generating activities; and that farmers' likelihood to engage in specific types of off-farm activities is determined by their risk and uncertainty attitudes.

Dedication

To smallholder farmers in Nigeria that chose not to quit farming despite the uncertainties and challenges.

Acknowledgement

My gratitude goes to my supervisors Professor Kelvin Balcombe and Dr. Ariane Kehlbacher for accepting to supervise my PhD to completion and for the guidance and consistent support that helped me in no small measure tackle the challenges as I conducted this research. Also special thanks to the staff of the Applied Economics, Marketing and Development in the School of Agriculture for the comments and feedback from the Annual Applied Economics, Marketing and Development (AEMD) postgraduate research conference which contributed to improving this work.

I especially thank Professor (Mrs) O'raye Dicta Ogisi an alumna of the University of Reading for setting high standards, challenging me and providing the platform that enabled this PhD become reality. I am also grateful to Barr. Rita Begho, Mr & Mrs Ireye and Mama Alice Begho for their contributions towards my education.

I gratefully acknowledge the Tertiary Education Trust Fund (TETFund) for partly funding this PhD and Delta State University Nigeria for granting me leave from work during the duration of studies. I express my gratitude to the staff of the Department of Agricultural Economics & Extension of Delta State University Nigeria for their encouragement and well wishes during the duration of my PhD. I also extend my gratitude to all respondents from various communities and enumerators from the Federal Ministry of Agriculture Nigeria led by Mr. Daubry Tare Philip for dedicating time to participate in the experiment and respond to the questionnaire. To my colleagues Rui Catarino, Raed Al-Ani, Juma Alanbari, Jose Vincente, Omotuyole Ambali, Milorad *Misha* Plavsic, Razan Majar Ponjan Pinpart, Heather Maggs and Ciro Dominguez-Mendez; I thank you for being very accommodating and for the useful conversations we shared over the years.

Special thanks to my Parents Mr and Mrs McDonald Begho and other members of my family especially Oyehmi & Abi Begho and Dr. Angie Unokesan for the kind hospitality throughout my duration of study here in the UK. Finally, my heartfelt gratitude goes to Mary Begho my lovely wife for putting her career on hold for mine and for the time dedicated to looking after our daughter in my absence.

Table of Content

List of Tables

List of Figures

List of Abbreviations and Acronyms

DM	-	Decision maker
EV	-	Expected value
FOD	-	First Order Stochastic Dominance
SOD	-	Second Order Stochastic Dominance
CPT	-	Cumulative Prospect Theory
RDU	-	Rank Dependant Utility
CEU	-	Choquet Expected Utility
EUT	-	Expected Utility Theory
DARA	-	Decreasing Absolute Risk Aversion
IRRA	-	Increasing Relative Risk Aversion
IPRA	-	Increasing Partial Risk Aversion
CRRA	-	Constant Relative Risk Aversion
PWF	-	Probability Weighting Function
OFIGA	-	Off farm Income Generating Activities
MV	-	Mean-Variance
MPL	-	Multiple Price List
PDF	-	Probability Density Function
SD	-	Standard Deviation
BD	-	Bipolar disorder
Resp.	-	Respectively
Vs.	-	Versus

Section 1- Introduction, Literature Review and Research Methods

Chapter 1

Background of the Study

1.0 Introduction

Hardly any 'real world' decisions are made without some degree of uncertainty and/or risk. Much has been reported about the risk attitudes[1] of people, including farmers, but there has been less attention to uncertainty. Yet, farming decisions are permeated with uncertainties ranging from - the unpredictable nature of weather, household health and government legislation - to fluctuating input and output prices. As a result, farmers' attitudes towards risk and/or uncertainty are pivotal to their decisions (Bard & Barry, 2001; Haneishi *et al.,* 2014; Bauer & Buchholz, 2008; Sengupta, 2012; Wang & Wang, 2012).

Numerous studies have now made contributions that provide insights into decision-makers' (DMs') attitudes to risk and uncertainty. These studies have been driven by multidisciplinary perspectives including mathematics, economics and psychology. Each are directed at examining and rationalizing risk and uncertainty attitudes. However, there is a lack of consensus on the estimation methods, suitable elicitation tools and techniques. Specifically, risky and uncertain decision-making theories and methods have not been exhaustively tested. Thus, the extent to which theories about uncertain and risky choice reflect actual behaviour is not fully known.

This study examines attitudes to risk and uncertainty by farmers in Nigeria and connects the findings with other important farm issues including the relationship between mental health related factors and risk or uncertainty attitudes; and the effect these attitudes to risk and uncertainty have on farmers' day-to-day decisions both for themselves and for others. The purpose of this chapter is to identify problems, motivate the research questions and guide the reader as to the specific objectives of this thesis.

[1] Attitudes in this context refers to a decision maker's mental disposition with respect to a state.

1.1 Problem Statement

Mixed inferences about risk and uncertainty attitudes and its implications

In the broader literature, the nomenclature of risk and uncertainty is not used in a standardised way. The applied literature uses the term risk, when it probably means uncertainty. The distinction between risk and uncertainty is discussed in section 2.1 of Chapter 2. However, at this point it is necessary to mention that the working definition of risk adopted in this thesis is a DM faced with a situation in which the associated probability density of realising outcomes is specified and the DM has this information. As for the case of uncertainty, the DM has insufficient information of the associated probability density but has information that one outcome within an interval will occur.

Farmers in developing countries have frequently been reported to have homogenous mostly 'risk-averse' attitudes. Several of these studies have also assumed that risk and uncertainty attitudes are personality traits thus it is stable across context and content domains (*e.g.* Eysenck & Eysenck, 1977; Paunonen & Jackson, 1996). However, much recently there has been disagreement about the risk attitudes of small farmers. Some authors have reported that - far from conforming to the stereotype of extremely risk averse that small farmers have often assumed to be – there is evidence that farmers may be *risk neutral* (as in Vieider, Truong, Martinsson, & Nam, 2013) or *risk seeking* (see Henrich & McElreath, 2002; Maertens, Chari & Just, 2014). These authors have argued in favour of domain-specific construct which implies individual are not consistently risk-taking or risk-averse across domains but that attitudes depend on the domain and 'size' of the prospects.

In Nigeria, a the Top-Down[2] approach is operated and farmers rely on the government for support; the assumed stereotypic 'risk averse' attitude of farmers by the government has influenced the nature of agricultural policies, projects and support of successive governments towards farmers. For example, in order to encourage production the marketing board policy provided a guaranteed return for

[2] The top-down approach refers to a system where all planning and intervention is at the national level without any participation in the decision making process by the farmers who are supposed to be beneficiaries. This method has the demerits of one-way flow of information without room for feedback (Agbamu, 2000).

farmers' produce though at prices substantially lower than market prices. However, in most cases the objectives of these policies are usually not met (Nwankwo & Wolfgang, 2008; Olubiyo *et al.,* 2009). One of the factors attributed to these failures (*e.g.* considering the case mentioned above where the post-marketing era witnessed higher production) has been poor situation assessment (Olarinde, Manyong & Akintola, 2010) and crucially the lack of consideration that risk attitude of farmers may be domain specific and dependent on the outcomes of the prospects[3].

It has been suggested in some studies (*e.g.* Isik, 2002; Cervantes-Godoy, Kimura & Antón, 2013) that for such policies to be effective (at the same time not being an additional source of institutional or policy risk), it must be attuned with farmers' risk attitudes. Therefore, there is a need to broaden the scope of research on small farmers' risk and uncertainty attitudes in Nigeria[4] across contexts and content domains. This motivates further investigation of farmers' risk and uncertainty attitude in order to provide plausible information that will serve as a guide to policy makers as well as strengthen the broader literature on risk and uncertainty.

Much has been reported about the risk attitudes of farmers in developing countries. However, studies on uncertainty are limited. It is evident that important farm decisions are taken under uncertainty as much as under risk. Several studies including Abdellaoui *et al.,* (2010) and Heath & Tversky (1991) have provided evidence that individual DM can differentiate between risky and uncertainty prospects and have distinct attitude to both. It could be that the sparse research in this area is a result of limited number of acceptable theories on which to model empirical findings (*e.g.* De Palmer *et al.,* 2008) on one hand, or to the proliferation of normative models that are unable to empirically describe the choices under uncertainty on the other hand.

---

[3] The context in which 'prospect' is referred to here is outcomes that have probability densities attached to it.

[4] Currently most studies in Nigeria have focused on determinants of risk attitude (e.g. Aye & Oji, 2007; Nmadu, Eze & Jirgi, 2012) or the effect of different variables such as income and consumption on risk attitude (Adewumi, Ayinde, Olatunji & Ajayi, 2012). Others estimated risk attitude from observed levels of products and inputs use (see Olarinde, Manyong & Akintola, 2007). Only a few have used psychometric scales on specific domains.

Making decision on behalf of others in Agriculture

Studies in the decision-making literature have focused on risk attitudes when making decision for oneself. However, in many situations, people make decisions on behalf of others. Crucially, this aspect has not received the much-needed attention. Proxy decision making in this context refers to making decision for someone on his/her request. Although decision by proxy is not widespread in agriculture as it is in medicine or public policy, there are also notable cases of such in farming. For instance in Nigeria, owing to the limited number of extension agents small farmers in most cases; have to work with opinion leaders or model/contact farmer who are in direct contact with extension agents. These opinion leaders reach decisions that may be binding for farmers, who share the consequences of such decisions. Given the evidence that risk attitudes have significant impact on decision (*e.g.* as documented in Domingo, Parton, Mullen, & Jones, 2015; Wossen, Berger & Di Falco, 2015; Tanaka, Camerer & Nguyen, 2016); and the negative consequence of a 'wrong' decision on entire livelihoods of smallholder farmers in developing countries; there is need to investigate further risk and uncertainty attitudes in proxy decision-making.

Biological/Physiological traits and Risk/Uncertainty Attitudes

Biological/physiological traits may influence risk and uncertainty attitudes; and may well be related to individuals' decision-making behaviour. However, limited number of studies have investigated the links between such factors and attitudes towards risk and uncertainty. There is literature suggesting that individuals with certain mood disorders are high goal-orientated and risk seeking. For instance, it is reported that in contrast to non-bipolar[5] individuals, those having bipolar disorder (BD hereafter) show impulsive behaviour (Johnson *et al.,* 2012; Reddy *et al.,* 2014) and become risk seeking/averse in certain states (Leahy, 1999). However, studies investigating the relationship between BD and farmers' risk or uncertainty attitudes is lacking. Although this link have not been given attention in developed countries,

[5] Bipolar Disorder (BD) commonly referred to as a mood disorder wherein episodes of both elevated and depressed mood is experienced by the individual and may be associated with distress and impairment of function (Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) 1994).

the reports that about 33% of adult Nigerians (compared to about 18.5% in the US[6] for instance) have suffered one form of mental illness (Owoyemi, 2013 *as cited in* Oyewunmi, Oyewunmi, Iyiola & Ojo 2015, Onyemelukwe, 2016; Suleiman, 2016) suggest the need for research in this area. More so, given the statistics that about 37% (*i.e.* approximately 70 million) of the Nigerian population are farmers (International Labour Organization, 2017), this thesis hypothesizes that a significant number of those predicted to be at risk of mental health related illness[7] in Nigeria could be farmers. It therefore becomes necessary to examine from these perspective whether mental health factors affects the Nigerian farmers' risk and uncertainty attitudes, which in turn can affect their livelihood.

Risk, uncertainty attitudes and the implications for farm decision

Small farmers especially in low/middle income countries are exposed to numerous uncertainties and risks but have fewer options to cope as formal institutions or policy instruments do not provide commensurate protection. Consequently, their livelihood is vulnerable. Off-farm employment has been documented as a significant risk coping strategy particularly among those who have the intent of cushioning production risk (Lamb, 2003) or the risk of income shortfall (Berg (2001); Mishra & Goodwin, (1997)). According to van Winsen *et al.,* (2014), risk seeking farmers are more proactive in their attitudes and strive towards curtailing risk through means such as farm diversification and farm business optimization. McNamara & Weiss (2001) posited that a key signal of risk aversion among farmers lies in the proportion of time spent on the farm enterprise and off-farm labour. However, not much of current research have focused on determining what links exist between farmers' risk and uncertainty attitudes and their farm and off-farm decisions. The closest studies to investigate this relationship are Bezabih, Gebreegziabher, GebreMedhin & Gunnar, (2010) and Iqbal, Ping, Abid, Kazmi & Rizwan, (2016). However, the details of experimental procedures used in the former to characterise

[6] Any Mental Illness (AMI) Among Adults. (n.d.). Retrieved September 6, 2016, from http://www.nimh.nih.gov/health/statistics/prevalence/any-mental-illness-ami-among-adults.shtm

7 Currently in Nigeria, the statistics showing the proportion of people having mental health related issues classified as BD is about 0.63% according to Institute for Health Metrics and Evaluation (IHME), 2017. This puts BD as the fourth prevalent mental and substance use disorders behind depression, anxiety, and alcohol use. See Appendix 10 for statistics on bipolar disorder in Nigeria.

risk preference is vague while for the latter, the experiments and methodology differ from this thesis.

Methodological issues

Several authors (including Schoemaker, (1993); Huber, Wider & Huber, (1997); Weber, Blais & Betz, (2002); Harrison, Humphrey & Verschoor, (2010)) have found that different models of choice and varing analytical design leads to different inferences about the risk attitudes of the DM. There are several reasons for these disparities, which includes differences in underlying theories, methodologies and elicitation techniques.

In order to model attitudes towards uncertainty of a DM, a number of methods have evolved in recent times. However, such theories and methods including Expected Utility theory (EUT), Prospect theory (PT), Rank Dependant Utility theory (RDU), Cumulative Prospect theory (CPT), Choquet Expected Utility (CEU), Salience theory (ST) and Regret and Disappointment theories have not been exhaustively tested. As such, the extent to which they reflect actual behaviour under risk and uncertainty is not fully known. Of particular concern is the gap in extending these theories to continuous prospects which partly triggered the need for this study. The procedure of most literature has mainly been willingness to pay (or accept) or use of lottery choices in discrete construct. There have been very limited studies that extend these popular theories to continuous prospects in experimental studies with exception of the works of Kothiyal, Spinu & Wakker (2011) *albeit* for Prospect Theory; Kontek (2009) for Relative Utility Theory; and Rieger & Wang (2006), Rieger & Wang (2008), Gürtler & Stolpe (2011), Tian, Huang & Wang (2012) for CPT.

Arising from the concerns regarding selection of the most appropriate theories and methodologies that best describes any DM's attitudes as well as the suitability of these methodologies in laboratory or field experiments, more research is necessary to provide additional evidence and broaden our understanding of the psychological construct of risk and uncertainty attitudes. This thesis therefore employs methodologies and unique experiments that represent the choices that DMs make day-to-day. Specifically, this study employs the CPT/CEU (equivalence of both theories under certain conditions is shown in section 3.4.2 in Chapter 3) to examine the risk and uncertainty attitudes across contexts and content domains.

1.2 Objectives

The broad objective of the study is to examine the risk and uncertainty attitude of a farm-household decision maker. *Content* domain in this thesis refers to the framing of the choice problems as either gains, losses or mixed (*e.g.* in terms of money; it may be solely a loss of money, a gain of money or having both the possibility of losing or gaining some money). While *contexts* domain gives meaning to the content domains by presenting different 'states' of the decision problem (*e.g.* monetary *vs* non-monetary context). Within these settings, this thesis specifically:

i. Examines farmers' risk attitudes in different context (monetary & time) and content (gain, loss & mixed) domains

ii. Examines farmers' uncertainty attitudes in different content (gain, loss & mixed) domains but within a specific context

iii. Compares attitudes to risk and uncertainty within content domains

iv. Examines and compare farmers' risk attitudes when making proxy decision and decisions for oneself.

v. Examines the relationship between mental health related factors and risk and uncertainty attitudes

vi. Investigates the relationship between risk and uncertainty attitudes and decision to participate in off-farm income generating activities.

1.3 Research Questions and Hypotheses

This study draws on the gaps that are identified in the literature in Chapters 2 and 3 and raises the following research questions and corresponding hypotheses.

1.3.1 Risk and Uncertainty Attitudes

Central to the Expected Utility theory (EUT) (discussed in section 3.1 of Chapter 3) is the estimation of risk attitude using the curvature of the utility function. From this perspective, some economists have generally taken attitudes towards risk as given and treated them as stable across context. On the other hand the rank dependant (RDU) based theories (including the CPT and CEU) which relies on both the utility function and probability weightings to explain risk attitude suggest that individuals are not globally risk-averse *i.e.* risk attitudes often differ across domains (the distinction between risk averse/seeking is presented in Section 2.1 in Chapter 2). The questions that arises are:

A. Do risk and uncertainty attitudes remain consistent within content domains (gain, loss, mixed)?

Increasing number of studies have shown that the way in which outcomes are framed influences DMs' preferences and risk/uncertainty attitudes. DM's are not expected to maintain the same attitude in different content domains *i.e.* being unswervingly risk/or uncertainty averse or seeking. Therefore, it is hypothesised in this research that:

Hypothesis 1: Attitudes to risk depends on content domains

Hypothesis 2: Attitudes to uncertainty depends on content domains

B. Do risk attitudes remain consistent across context (monetary *versus* time) domains?

Numerous studies suggest that risk attitude is context domain-specific. Such studies have provided evidence that challenges the perspective of risk attitude as a personality trait and shown the reason why such models are unreliable in predicting attitudes across context. Based on this viewpoint, the corresponding hypothesis that is tested is:

Hypothesis 3: Attitudes to risk depends on context

C. Do attitudes to risk differ from attitudes to uncertainty (within a particular context)?

On one hand, there has been definitional and operational inconsistency in using the terms risk and uncertainty interchangeably in literature that has led to different conclusions while on the other hand there are studies that suggest the behaviour of an individual DM under risk is different from that of uncertainty. It is hypothesised that:

Hypothesis 4: Attitudes to risk compared to uncertainty are different

Although similar hypotheses have been tested (for example in Weber, Blais & Betz, 2002; Blais & Weber 2006; Hanoch *et al.,* 2006; Zimmerman *et al.,* 2014; Gummerum *et al.*, 2014; Rolison *et al.,* 2014 among others), however the experiment design, elicitation methods analytical techniques differ from this study.

1.3.2 Risk Attitude in Proxy Decision

In proxy decision-making – a case where one is permitted to make decision on behalf of others; the proxy is often regarded as having better knowledge or information in that specific domain in which the decision is to be made (Harvey *et al.,* 2006). The proxy is however expected to put into consideration the risk tolerance of the person on whose behalf the decision is being made. For example, a farmer may request the veterinarian to make decision for him regarding specific treatment for his animals. There have been numerous justifications to back the reason why proxy decision may differ from personal decision within the context of risk. Specifically, Stone, Yates & Caruthers (2002) posit that it could be based on an assumption of difference in risk attitude between the proxy and recipient and the possibility of making the decision to meet different aims under both situations. Based on similar assertions, the questions that arise are: Does a proxy's own risk attitude influence the decision taken for others? Do proxies categorise others as more risk or uncertainty averse than they are? This leads to the more specific research question:

D. Does a DM's attitude to risk differ when they take decision for others?

The hypothesis tested from the above question is:

> *Hypothesis 5: There is significant difference in a DM's risk attitude when making personal vs. proxy decision.*

1.3.3 Effect of Bipolar Disorder on Risk and Uncertainty Attitude

Leahy (1999) opines that BD individuals tend to enjoy gains more and suffer losses less than non-BD individuals. That is, at the manic phase, the threshold for defining loss (gain) is high (low) and the individual could be categorised as risk-seeking. Leahy (1999) further asserts that during the manic phase, individuals view themselves as possessing unlimited current and future resources, and trust their "flawless" prediction and control of outcomes. Similarly, Chandler *et al.,* (2009) reports that bipolar disorder individuals are more risk-seeking for increased gains. In the light of these arguments, this study seeks to determine the effect of bipolar disorder on risk and uncertainty attitude. The specific research question to be addressed is:

E. Is there any effect of bipolar disorder on risk or uncertainty attitude?

It is hypothesised in this thesis that:

Hypothesis 6: DMs having bipolar disorder tendencies have significantly different risk and uncertainty attitude from DMs with no bipolar disorder.

1.3.4 Risk and Uncertainty Attitudes and Off-farm Income Generating Activities

According to the assertion of Reij & Waters-Bayer (2001) creative and innovative farmers typically farm the land to meet their needs thus do not depend to a large findings of Baron (2011) that overly risk-seeking individuals characteristically fail to diversify. Arguably, the proposition is that risk seeking farmers would be mostly full-time farmers who may be less likely to diversify to off-farm income activities. From these perspectives, the specific research question and hypothesis which is put forward is:

F. Is there any relationship between the risk attitudes and the decisions to engage in off-farm income earning activities?

The corresponding hypothesis that is tested is:

Hypothesis 7: Farmers that are risk seeking in monetary context are less likely to engage in off-farm employment

1.4 Outline of the Thesis

The thesis is made up of the following sections. While Chapter 1 introduces the study, Chapter 2 covers literature review. Chapter 3 deals with the theories of risk and uncertainty. In Chapter 4, research methods and models are presented while Chapter 5 documents the survey design and implementation. Chapter 6 reports the description of data, Chapter 7 covers results of CPT/CEU, Chapter 8 contains the results of alternative theories, Chapter 9 dwells on the implication of findings for farm decisions and Chapter 10 summarises, concludes and provides recommendations for policy design.

Chapter 2

Risk and Uncertainty Attitudes in Farmers' Decision Making

2.0 Introduction

This chapter is a discourse on risk and uncertainty attitudes of a DM in the broad context with the focal point being attitudes to risk and uncertainty of farmers responsible for making farm decisions. It reviews the approaches to eliciting attitudes to risk and uncertainty as well as examines literature on the role of risk and uncertainty attitudes on farmers' decision-making. In addition, this Chapter investigates how much is known about risk attitudes in proxy decision-making in the context of farmers in developing countries. Finally, it reviews studies on the relationship between mental health related factors and farmers' risk attitude, risk/uncertainty attitudes and the decision to engage in off-farm income earning activities and; identifies the links between risk/uncertainty attitudes and type of off-farm activity chosen.

Specifically, the sections that make up Chapter 2 are as follows. Section 2.1 covers the meaning of risk and uncertainty and the specific context adopted for use in this thesis, section 2.2 focuses the empirical evidence of risk and uncertainty at the farm level while section 2.3 examines previous studies on risk and uncertainty attitudes in proxy decision making. In section 2.4, literature on bipolar disorder and risk attitude are discussed; while risk attitude and its relationship with off-farm participation are reviewed in section 2.5. Finally, the last sections in this chapter dwell on the elicitation tools and methods that have been reported in the risk and uncertainty literature.

2.1 Distinction between Risk and Uncertainty

'Risk' and 'uncertainty' are fundamental terms in decision-making framework however different schools of thought hold different perceptions of risk and uncertainty. Therefore, it is difficult to have an all-inclusive definition specifically as the nomenclature of risk and uncertainty has not been used in a standardised way.

Knight (1921) proposed one of the very early distinctions between risk and uncertainty. Knight defined risk as a condition where a decision maker (DM hereafter) is faced with a situation in which the DM knows every consequence of the decision but does not know prior to decision-making the events that will in reality occur. This implies that the DM can measure the odds with accuracy to the extent that the prediction will be similar to any other DM having identical information and beliefs. Knight (1921) then distinguished risk from uncertainty from the perspective of incomplete knowledge by defining uncertainty as a situation in which the all possible outcome of a given state is unknown to a DM thus the DM cannot measure the odds with any accuracy due to insufficient information. Building on the explanation put forward by Knight (1921) this thesis adopts a definition modified to fit prospects with continuous distributions. Risk refers to a situation where a DM is faced with a scenario in which the DM knows the associated probability density of realising an outcome. As for the case of uncertainty, the associated probability density is unknown but a DM has the information that an outcome within the specified interval would be realised.

To shed more light on the distinction between this definitions of risk and uncertainty, consider a hypothetical risky situation where a DM is presented with two prospects (Prospect A can earn the DM any amount between $4 and $7 and B is between $2 and $11). Assuming all outcomes over the interval have *equal likelihood* of occurrence, a uniform probability density is thus specified thereby making this a case of risk. However, for uncertainty the DM is aware that one outcome within the specified interval (*e.g.* in the above hypothetical prospects A and B) would be obtained but the associated probability density (as to whether outcomes were '*equally likely*' or not) is not given.

Unlike other studies (*e.g.* Mas-Collel, Whinston & Green, 1995 and Jehle & Reny, 2000) that use the terms risk and uncertainty interchangeably this thesis adopts the above definitions to distinguish risk from uncertainty. This distinction is useful since there is empirical evidence in some other literature that the behaviour of an individual DM under risk is different from that of uncertainty (see Camerer & Weber (1992); Tversky & Fox (1995); Dow & da Costa Werlang (1992) that empirically distinguished between attitudes to risk and uncertainty in their studies).

2.1.1 Distinction between Uncertainty and Ambiguity

Notably, numerous studies have erroneously used the terms uncertainty and ambiguity interchangeably. Some studies (for example Backus, Ferriere & Zin, 2015; Fujino *et al.,* 2017) have argued that uncertainty consist of two main elements which these studies refer to as 'risk' and 'ambiguity'. In the literature, the perception of 'information gap' is what shapes many definition of ambiguity. Ellsberg (1961) argued that ambiguity is a condition that sits between two extreme conditions namely risk and absolute ignorance (a case where the DM has no information whatsoever on the relative probabilities). According to Camerer & Weber (1992) when important information that could be known is missing and it results in uncertainty about probability, this condition is referred to as ambiguity.

Earlier studies including Meyerson & Martin (1987), McCaskey, (1982) and Schrader, Riggs & Smith (1993) distinguished between uncertainty and ambiguity by classifying uncertainty in terms of shortage of information; and ambiguity from the perspective of absence of clarity with reference to the functional relationships between variables. From the above perspective, gathering additional information may lead to the situation of uncertainty being resolved however, it will not lead to resolving ambiguity.

Some studies[8] have argued that while the probabilities in the case of uncertainty are either unknown or indeterminable and ascribable to randomness or data limitations; the probabilities of ambiguity on the other hand are either not known

[8] These arguments can be found in studies including Dequech (2000); Camerer & Weber (1992) and Frisch & Baron (1988).

or indeterminable owing to data or model deficiency (yet with possibility in some cases to be known to persons other than the DM).

It is pertinent however to differentiate between uncertainty (in the context of this study) and ambiguity specifically as each require different procedure for problem-solving and behaviours differ under both (for example as reported in Schrader, Riggs & Smith, 1993; Saint-Charles & Mongeau, 2009). For clarification regarding the use of these terms in this thesis, uncertainty refers to the situation where the associated probability density is unknown but a DM has the information that an outcome within the specified interval would be realised. Ambiguity on the other hand viewed from the perspective of '*uncertainty about the uncertain;*' refers to the situation in which the DM does not have complete information about the associated probability density and the specified interval from which an outcome would be realised. In other words, the DM lacks sufficient information to establish a unique subjective belief distribution and is to any extent unable to define a probability distribution.

2.1.2 Defining Risk Aversion and Risk Seeking[9]

It is complicated to present a universally acceptable definition of 'risk averse' or 'risk seeking' especially as different assumptions and conditions result in different definitions. Therefore, this section provides background on the common definitions in the literature and highlights their respective limitations. It concludes by clarifying the context in which this study refers to 'risk averse' or 'risk seeking', how this definitions differ from several in the literature and the justification for choosing it above the others.

It is commonplace to find in the literature risk averse/seeking used loosely to describe DMs attitudes without acknowledging the role that context and content domains as well as magnitude of the prospects plays in determining the risk averse/seeking attitudes of a DM. This is because the premise on which such studies base their augments are maximisation of expected utility and global concavity or convexity of the utility/value function. In the absence of one or both conditions, the complexity around defining the terms (risk averse/seeking) increases.

In the case of Cumulative Prospect Theory (CPT) (details in Section 3.4 in Chapter 3) which is built around probability weighting and local convexity and concavity in the same value function, the meaning behind the concepts risk averse/seeking becomes fuzzy. On one hand, the literature have restricted the terms to the shape of the value function *albeit* acknowledging that the magnitude of the prospects determines risk averse/seeking attitudes. On the other hand, researchers have based it upon the overall attitude of DMs in connection with the actions taken when faced with "risky prospects".

What then is a risky prospect?

Of central importance in defining risky prospect is second order stochastic dominance (see Appendix 7 for details of first and second order stochastic dominance). Given two prospects A and B having CDFs F_A and F_B, assuming $\int_{-\infty}^{x}[F_B(x) - F_A(x)]d(x) \geq 0$ for all values of x and $F_B(x^*) - F_A(x^*)$ for some x^*

[9] I acknowledge the discussions and comments of Professor Kelvin Balcombe in building up these arguments.

then prospect A dominates B from the position of second-order stochastic dominance (SODs). From this perspective, risk ordering emerges such that A can be categorised as '*less risky*' if A SODs B. Accordingly, definitions of risk aversion can be drawn.

Definition 1 *A DM is termed GLOBALLY risk averse if for any two prospects A and B for which A SODs B the DM will always choose A.*

However in the case of risk seeking, the converse holds if A and B have equal means. Thus, risk seeking is defined with respect to controlling for the mean; therefore making it pertinent to introduce the concept of mean preserving spread (MPS). B is a mean preserving spread of A $if and\ only\ if$ A SODs B and A and B have identical expected values *i.e.* $E\ (A)\ =\ E\ (B)$.

Modifying *Definition 1* leads to

Definition 2 *A DM is GLOBALLY risk averse if for any two prospects A and B for which B is a MPS of A the DM will always choose A.*

Definition 3 *A DM is GLOBALLY risk seeking if for any two prospects A and B for which B is a MPS of A the DM will always choose B*

Following the inference in the literature, under Expected Utility Definitions 2 and 3 suggest global concavity or convexity of the utility function. Crucially, however, the curvature of the value function is not given consideration in both definitions. Definitions 2 and 3 can be broadened to domain specific payoffs such that if the payoffs of A and B are both within payoff domain $\mathbb{D}$ then

Definition 4 *A DM is GLOBALLY risk averse in payoff domain* $\mathbb{D}$ *if for any two prospects A and B, the payoffs of A and B are both within payoff domain* $\mathbb{D}$ *and for which B is a MPS of A the DM will always choose A.*

Definition 5 *A DM is GLOBALLY risk seeking in payoff domain* $\mathbb{D}$ *if for any two prospects A and B, the payoffs of A and B are both within payoff domain* $\mathbb{D}$ *and for which B is a MPS of A the DM will always choose B.*

These definitions also hold within the context of the EUT given that if a DM's utility function is uniformly concave/convex within payoff domain $\mathbb{D}$ then the DM will be risk averse/seeking within that domain. The assertion above is not transferable to the CPT, owing to the fact that concavity/convexity over the specified domain is no longer sufficient for risk aversion/seeking behaviour. Thus, a DM can be risk averse at the same time optimistic in terms of probability weightings.

An extension of the above definitions may require defining a probability-payoff domain $\Omega = \mathbb{D}, \mathbb{P}$ resulting in

Definition 6 *A DM is risk averse in probability-payoff domain* Ω *if for any two prospects A and B, the payoffs and probabilities of A and B are both within domain* Ω *and for which B is a MPS of A the DM will always choose A.*

Definition 7 *A DM is risk seeking in probability-payoff domain* Ω *if for any two prospects A and B, the payoffs and probabilities of A and B are both within domain* Ω *and for which B is a MPS of A the DM will always choose B.*

However if the sub-domains within Ω over which the DM is risk averse/seeking is ambiguous, then it heightens the complexity in defining risk aversion and risk seeking.

Based on the above arguments, this thesis therefore adopts the definition of risk aversion in respect of the curvature of the value function. However, is should be noted that this is not equivalent to DMs choosing prospects based on mean preserving spreads. The rationale behind the focus mainly on the curvature of the value function in describing risk aversion/seeking is that the manner in which DMs treat probabilities (known as optimism and pessimism in the decision-making literature and discussed in 3.4.2 in chapter 3) is not often a reflection of DMs preferences *per se*. Therefore, a DM can be risk averse (concave in utility over the domain) at the same time optimistic in terms of probability weightings[10] such that within the context of the above definitions, the DM is not risk averse.

[10] Evidence of this behaviour is reported in Balcombe & Fraser (2015) where respondents are estimated to be risk averse as regards the concave value function on one hand but on the other hand are optimistic as to high payoffs with high probability.

2.2 Empirical Evidence on Risk and Uncertainty at Farm Level

Like other enterprises, farm businesses are faced with uncertainty (and possibly risk) which is crucial in determining the possibility of a farmer achieving his/her farming objectives. Although in reality farmers deal with uncertainties far more often; the literature has paid less attention to uncertainty compared to risk. The prominence of risk studies over uncertainty has meant that empirical findings about uncertainty are limited. In the broader literature, (see Boehlje & Trede, 1977; Heifner, Coble, Perry & Somwaru, 1999; Hardaker, Huirne, Anderson, & Lien, 2004) the main uncertainties in agriculture have been classified into five main groups. First, production uncertainties arising from the uncertain natural growth processes of crops and livestock including weather related factors. Second, price or market uncertainties due to unpredictable changes in prices of both inputs and outputs. Third, financial uncertainties and fourth, institutional uncertainties resulting from uncertainties surrounding income/profit and government actions respectively. Fifth, human or personal uncertainties arising from problems with human health or personal relationships. These uncertainties in several applied literature (*e.g.* Hardaker 2004; Patrick 1998; Huirne *et al.,* 2000); have either been erroneously referred to as risk or both terms have been used interchangeably.

According to Kaan (1998), the most significant of these uncertainties are prices and yield variability which makes farmers perceive farming as a "*gamble*" since at the onset of the farming season there is no certainty that their efforts will pay off. Hoogeveen *et al.*, (2004) find that farm households in developing countries are typically more exposed to uncertainties and risks compared to other enterprises however, the formal institutions or instruments do not provide commensurate protection. In Nigeria, the case is not different as smallholder farmers who are among the poorest in the country (Ajibefun, 2002; Asogwa, Umeh & Ihemeje, 2012) have to make decisions under conditions of uncertainties and risk while these small farmers typically have limited access to insurance markets; and market failures further amplify farmers' exposure to risks and uncertainty.

Using decision-making experiments applied to a number of methodologies, DM are commonly categorised as risk averse, risk neutral or risk seeking. Adopting different theories and assuming various utility functions parameters (discussed in section 3.1

in Chapter 3) across a wide range of countries as summarized in Table 1, farmers have mostly been reported as being risk averse to risk neutral (*i.e.* DM being indifferent to risk taking). However, a few studies have also found risk-seeking attitude among farmers. For example as shown in Table 1, while Yesuf, & Bluffstone, (2007) and De Brauw, & Eozenou (2014) find that farmers in Ethiopia and Mozambique are risk averse, Maertens, Chari, & Just (2014) and Henrich & McElreath (2002), in different studies in India and Tanzania respectively document farmers in those regions as risk seeking. While some of these researches find genuine difference in the attitudes of DMs, differences in underlying theories and differences in methodologies could have considerable effect on the results reported.

Table 1
Selected studies classifying low and middle income countries farmers' and rural households according to risk attitudes

Studies	**Countries**	**Framework/ Theories***	**Findings** (gains domain)
Yesuf & Bluffstone (2007)	Ethiopia	EUT	Risk averse
Binswanger (1980)	India	EUT	Risk averse
De Brauw & Eozenou (2014)	Mozambique	EUT & RDU	Risk averse
Akay, Martinsson, Medhin & Trautmann (2012)	Ethiopia		Risk averse
Vieider, Truong, Martinsson & Khanh (2014)	Vietnam	PT	Risk Neutral
Maertens, Chari & Just (2014)	India	EUT	Risk Seeking
Henrich, & McElreath (2002)	Tanzania	EUT	Risk Seeking
Ullah, Shivakoti & Ali (2015)	Pakistan	ELCE	Risk averse
Tanaka et al. (2010)	Vietnam	EUT, CPT	
Liu (2013)	China	CPT	
Harrison et al. (2010)	Ethiopia, India & Uganda	EUT CPT	Risk averse Risk Seeking
Hill (2009)	Uganda	EUT	
Miyata (2003)	Indonesia	EUT	
Wik et al. (2004)	Zambia	EUT	Risk averse
Dillon & Scandizzo, (1978).	Brazil	EUT	Risk averse
Gonzalez-Ramirez, Arora & Podesta (2018)	Argentina	EUT, CPT	Risk averse
Freudenreich, Musshoff & Wiercinski (2017)	Mexico	EUT, CPT	Risk averse
Galarza (2009)	Peru	EUT, CPT	
Ward & Singh (2014)	India	CPT	Risk averse
Liebenehm & Waibel, (2014)	Mali & Burkina Faso	CPT	Risk averse

Mao, Wang, Oniki, Kagatsume & Yu (2016)	China	EUT	Risk averse
Love et al. (2014)	Kenya	EUT, CPT	Risk averse
Kibet, Obare & Lagat (2018)	Kenya	EUT, CPT	Risk averse
He, Jin, Gong & Tian (2019)	China	CPT	Risk averse
Alvarado, Ibanez & Brummer (2018)	Chile	CPT	Risk averse
Serfilippi, Carter & Guirkinger (2015)	Burkina Faso	EUT, CPT	Risk averse
Ihli, Chiputwa, & Musshoff (2016)	Uganda	EUT	Risk averse
Brick, Visser & Burns (2012)	South Africa	EUT	Risk averse
Holden & Quiggin (2015)	Malawi	EUT, CPT	Risk averse
Petraud, Boucher & Carter (2015)	Peru	EUT, CPT	Risk averse
Orhan, Vedat, Ahmet & Zeki (2016)	Turkey	ELCE	Risk averse
ZgaJnar & Kavcic (2011)	Slovenia	MV	Risk averse
Torkamani & Haji-Rahimi (2010)	Azerbaijan	EUT	Risk averse
Other studies classifying high income countries farmers' according to risk attitudes			
Bocquého, Jacquet & Reynaud (2013)	France	EUT, CPT	Risk averse
Bougherara, Gassmann, Piet & Reynaud (2017)	France	EUT, CPT	Risk averse
Gregg & Rolfe (2017)	Australia	EUT, RDU, CPT	Risk averse
Tauer (1986)	US	EUT	Mixed findings
Roe (2015)	US	Self-assessment	Mixed findings
Meraner & Finger (2017)	Germany	Self-assessment, EUT	Risk averse
Xu et al. (2005)	US	Psychological measurement scales	Risk seeking
Canales et al. (2015)	US	EUT, CPT	Risk averse
Other studies classifying DMs (non-farmers) according to risk attitudes			
Tversky & Kahneman (1992)	US	CPT	Risk averse
Wu & Gonzalez (1996)	US	CPT	Risk averse
Wakker, Erev & Weber(1994)			
Harrison & Rutström (2009)	US	EUT, CPT	Risk averse
Stott (2006)	UK	CPT	Risk averse
Balcombe & Fraser (2015)	UK	RDU, CPT	Risk averse
Loomes & Sugden (1998)	UK	EUT	Risk averse
Tu (2005)	Sweden	CPT	Risk averse

Hey & Orme (1994)	US	EUT	Risk averse
Donkers et al. (2001)	Netherlands	EUT, CPT	Mixed findings
Bruhin et al. (2010)	Switzerland China	CPT	Risk averse
Zeisberger et al. (2012)	Germany	CPT	Risk neutral
Toubia et al. (2013)		CPT	Risk averse
Abdellaoui et al. (2005)	Germany	CEU, CPT	Risk averse
Booij et al. (2010)	Netherlands	EUT, CPT	Mixed findings
Camerer (1989)		EUT	Risk averse

EUT – Expected Utility Theory
RDU – Rank Dependant Utility Theory
PT – Prospect Theory
ELCE – Equally Likely Certainty Equivalent approach
MV – Mean-variance Expected utility
CEU – Choquet Expected Utility Theory
These theories are extensively discussed in chapter 3

Further, several studies have identified links between attitudes towards risk/uncertainty and agricultural decision-making. These links covers farmers decisions to adopt new technology (see Asci, Borisova & VanSickle, 2015; Liu, 2013; Marra, Pannell & Ghadim, 2003; Kebede, Gunjal, & Coffin, 1990). The decision to take insurance (see Kouame, & Komenan, 2012; Amaefula, Okezie & Mejeha, 2012), the decision to hedge (see Rolfo, 1980), the decision to sharecrop (Reid, 1976), the decision to comply with environmental policies (Ozanne, Hogan and Colman, 2001; Brick, Visser & Burns, 2012) – to the relationship between risk and farm productivity (Barrett, 1996). All of these studies have lent a hand to accentuate the importance of understanding and accurately predicting risk and uncertainty attitudes.

2.3 Risk Attitudes in Proxy Decision Making

Most of the studies in the decision-making literature have focused on risk attitudes when making decision for oneself. However, in many situations, people make decisions on behalf of others *i.e.* proxy decision-making wherein decision is made for another person on his/her request. Given the importance of some of these proxy decisions there are reasons to examine what similarities or differences exist when the decision is made on behalf of another person compared to decision for self.

In Nigeria, farmers are sometimes in the position where they make decisions on behalf of other persons. Owing to the limited number of extension agents, small farmers in most cases have to work with opinion leaders or contact farmer who are in direct contact with extension agents. These opinion leaders reach decisions that may be binding for farmers; who share the consequences of such decisions. There are arguments in the literature whether attitudes in proxy decisions differ from personal decision within a specific context under risk and uncertainty. Studies including Ockenfels (2010), Chakravarty *et al.,* (2011), Polman (2012), and Stone *et al.,* (2013), provide support for the argument that a DM's attitude to risk differs in proxy compared to self. On the other hand, Kvaløy & Luzuriaga (2014) and Humphrey & Renner (2011) have reported contrary findings.

Social psychology lends different explanations as to why personal and proxy decisions might differ when approached from different perspectives. These perspectives are discussed as follows.

2.3.1 Responsibility

Responsibility within the context of decision-making refers to a situation in which the decisions made affect both the decision maker and the person on whose behalf the decision is being made. Therefore, the proxy considers not only the processes and outcomes but also the consequences. It is typically in the form of a principal-agent relationship where in several cases both the principal's and agents payoff depends on the outcome of the decision taken by the agent. For example, in farming context this would be a contact farmer primarily responsible for contacting and communicating with extension agents in addition to being responsible for making decision on behalf of other farmers.

Most studies find that responsibility has a significant effect on risk and uncertainty attitude. For example, Kvaløy, Eriksen & Luzuriaga, (2014) reports that personal decisions made by individuals are different compared to those made on behalf of others. Charness & Jackson (2009), Fullbrunn & Luhan (2015), Bolton, Ockenfels & Stauf (2015) and Pahlke *et al.,* (2015) find that proxy decision where responsibility was attached had significant effect on the decision made by the proxy. However the direction of the effect of responsibility (*i.e.* whether responsibility increases or decreases risk or uncertainty aversion) when making decisions has been mixed. As presented in Table 2, Chakravarty *et al.,* (2011) and Agranov *et al.,* (2014) studies show that responsibility increases risk-taking; Bolton & Ockenfels (2010), Vieider *et al.,* (2016) conclude that responsibility increases risk aversion while Humphrey & Renner, (2011) found no effect of responsibility on risk attitude when making decision for others. While these differences may be genuine, there is also the possibility that outcomes were driven by the design of the task and the estimation methods.

As for the effects of responsibility for choices specifically in the gains only domain, the findings in this area have also been mixed. For instance, Bolton and Ockenfels (2010), Humphrey and Renner (2011), Anderson *et al.,* (2015) do not find decisions under responsibility to significantly influence choice behaviour in the gain domain, Bolton *et al.,* (2015) and Pahlke *et al.,* (2015) reports otherwise. Most studies have focused mainly on financial decisions with discrete monetary outcomes, however there are reasons to extend the scope, elicitation method and category of respondents *e.g.* to DMs using continuous 'prospects' which is where this thesis fills the gap.

2.3.2 Accountability

According to Semin & Manstead (1983) and Tetlock (1992), accountability refers to the (implicit or explicit) expectation of a proxy that any decision he or she takes needs to be justified to the individual(s) on whose behalf the decision is being made prior to or post decision making. In the agricultural context, this could be a farmer responsible for managing and taking decisions on resources on a communal farm or joint enterprise. For example, in Fadama III rural agriculture project in Nigeria, the proxy is the project leader who make binding decisions such as the types of farm/off-farm investment the group engages in or whether to adopt certain technologies. Given the fact that the DM can be 'blamed' for the decision, *a-priori* it is expected that when making risky decisions for others the DM will consider this factor.

In social psychology, researchers have made efforts to prove the effects of accountability on decision making as shown in Table 2. Holding DMs accountable for their decisions has been reported to be a credible means to de-biasing loss aversion in self-proxy relations. Studies including Pahlke, Strasser & Vieider, (2012) introduces accountability post-experiment while others *e.g*. Sutter (2008) focused on agent justifying any decision taken prior to decision-making. Sutter (2008) conclude that accountability increases risk seeking. Similarly, Schlenker (1991) reported amplified risk attitudes under accountability for either risk lovers who preferred more risky choices or risk averters who became more cautious. In contradiction, Humphrey & Renner (2011) findings suggest preferences of individuals in the gain and loss domains are unaffected by accountability. Crucially, the domains and size of the prospects; as well the social distance that exist between the proxy decision maker and the person on whose behalf the decision is being made may have resulted in mixed finding reported in these studies.

2.3.3 Self-Other Distance

Self-Other distance – the social distance between others and self can provide some explanations as to why attitudes to risk may differ when taking decisions for oneself compared to proxy decisions. There have been proponents and opponents in the discourse on the effect of self-other differences in decision making under risk and uncertainty. Two widely mentioned explanations for self-other differences in decision making are social value theory[11] and construal level theory[12].

The proponents of social value theory argue that when making proxy decision under risk or uncertainty, the individual assigns social value over and above other factors as opposed to decision for self where there is a mix of other elements. According to Stone & Allgaier, (2008) the emphasis is on what is 'socially valued' as opposed to what the individual making the decision would do in a scenario where decisions are not socially-sanctioned. In conditions where value is placed on risk aversion (for instance in outcomes with life-threatening consequences), several studies have documented safer decisions for others than for the self. As shown in Table 2, Stone, Choi, de Bruin & Mandel, (2013) findings support this expectation as they show that DM's display greater risk-aversion for others than for self in situation where social value is placed on risk aversion.

On the other hand Construal level theory (CLT) surmises that individual's behaviour is impacted upon by psychological distance that determines the way in which future events are mentally portrayed. Self-other distance in this context is based on the concept of social distance that describes the affective closeness between the DM or proxy and the individual(s) on whose behalf the decision is to be made. According to Zhang *et al.,* (2017), the more psychologically removed the DM is from the other person on whose behalf the decision is to be made, the greater the social distance. From this perspective, Zhang *et al.,* (2017) found that self-other distance increased risk aversion. Raue, Streicher, Lermer, & Frey (2015) found that construal level does not have a similar effect across domain as their results show no effect in the loss domain contrary to what was obtained in the gain domain. However, there are

[11] See Stone, Choi, de Bruin & Mandel, (2013) for detailed discussion
[12] In the works of Trope, Liberman & Wakslak, (2007); Trope & Liberman, (2010); Raue, Streicher, Lermer, & Frey (2015) the construal level theory extensively discussed and tested.

concerns about the psychological distance hypothesis in explaining empirical findings and the simplicity of the CLT to form a generally accepted theoretical model.

Table 2
Selected Literature on Risk Taking for Others (Proxy Risk)

Studies	**Contexts**	**Findings**
Chakravarty *et al.,* (2011)	*Responsibility*	Increased risk seeking
Pollmann,*et al.,* (2014)	*Accountability*	Increased risk seeking
Polman (2012)	*Responsibility*	Increased risk seeking
Agranov *et al.,* (2014)	*Responsibility*	Increased risk seeking
Reynolds *et al.,* (2009)	*Responsibility*	Increased risk aversion
Eriksen & Kvaløy (2010)	*Self-Other distance*	Increased risk aversion
Vieider, *et al.*, (2016)	*Responsibility*	Increased risk aversion
Sutter, (2009)	*Accountability*	Increased risk seeking
Lion & Meertens, (2001)	*Accountability*	Mixed findings
Zhang *et al.,* (2017)	*Self-Other distance*	Increased risk aversion
Humphrey & Renner, (2011)	*Responsibility*	No effect
Charness & Jackson (2009)	*Responsibility*	Increased risk aversion
Weigold & Schlenker (1991)	*Accountability*	Increased risk aversion
Bolton & Ockenfels (2010)	*Responsibility*	Increased risk aversion
Stone, Choi, de Bruin & Mandel, (2013)	*Self-Other distance*	Increased risk aversion

2.4 Bipolar Propensities and Risk and Uncertainty Attitudes

Economists have generally taken attitudes towards risk and uncertainty as given; and treated them as stable. An alternative perspective is that the causes of these attitudes to risk and uncertainty is worthy of investigation. Moreover, these attitudes may be temporally variable and related to biological/physiological traits of individuals. Accordingly, decision-making behaviour is likely to be related to mental health related factors such as 'bipolarism', yet for the most part economists have not investigated the links between such factors and attitudes towards risk and uncertainty.

With mental health issues being more prevalent than previously reported[13] (probably due to more individuals contacting mental health services as a result of increased awareness and reduction in stigma and discrimination); studies focused on examining mental health related factors and decision-making have become more requisite. Notable, the impact of mental health related issues is largely discernible in occupational functioning and a 'wrong' decision can threaten the entire livelihood of DM's (especially many smallholder farmers in developing countries that are barely 'hanging in'). Thus, examining the effect mental health related factors (with focus on bipolar disorder in this thesis) has on a DM's attitudes to risk and uncertainty will help to better understand the potential drivers of risk/uncertainty attitudes as well as ensure appropriate interventions are targeted at assisting individuals' with mental health problems when they are faced with making important decisions.

Bipolar Disorder (BD) commonly referred to as a mood disorder wherein episodes of both elevated and depressed mood is experienced by the individual and may be associated with distress and impairment of function (Diagnostic and Statistical Manual of Mental Disorders (DSM-IV), 1994). An individual with this disorder experiences episodes of depression and mania referred to as bipolar I disorder (or hypomania – bipolar II disorder) which occur in turns (National Health Service (NHS) 2011). These extreme changes in mood either from highs to lows or *vice versa* can persist for hours, days or even months (Ogoke, Nduka & Nja, 2015). Chandler,

[13] See Duncan & Prowse, (2014), Blader & Carlson, (2007).

Wakeley, Goodwin & Rogers, (2009) affirms that risky behaviour can be linked with Bipolar disorder (BD). During the period of "highs" the individual is reported to have increased self-esteem, increased goal-directed activities and becomes more risk seeking.

According to Johnson *et al.*, (2012); Reddy *et al.*, (2014) one of the distinctive features of bipolar disorder is impulsive behaviour and increased propensity to work toward a reward, usually in the absence of any adequate plan. However, Mason *et al.,* (2014) asserted that bipolar disorder is like a double-edged sword. It aids the individual to strive toward their goals and ambitions and may consequently lead to success. However, the fact that most decisions may be driven by immediate benefit usually result to adverse effect. It is also documented that during manic and depressive episodes, decisions made by individuals with bipolar disorder are typically suboptimal and can have negative long-term consequences. However, this argument contradicts Tremblay, Grosskopf & Yang (2010) who find evidence of links between bipolar disorder and occupational creativity and reports that productivity gains from enhanced creativity may have the capacity to outweigh productivity losses from bipolar illness. Nevertheless, attempts have been made to show that in comparison to a DM without mental health problems, the tendency towards risk-taking behaviour would increase the proportion of risky choices taken by a bipolar disorder DM.

Although BD has received much research attention in developed countries, a very limited number of studies have been carried out in developing countries. In Nigeria, almost all studies so far has been targeted only at diagnosed and hospitalized patients across Federal Neuropsychiatric Hospitals (see Onyeama, Agomoh & Jombo, 2010; Aiyelero, Kwanashie, Sheikh, & Hussaini, 2010) with the exception of Gureje & Lasebikan, 2006 who carried out a large sample study on 4,948 respondents and finds that 17.9% had at least one DSM–IV[14] disorder. Aiyelero *et al.,* (2010) report that, in Nigeria symptoms of all such illness are considered embarrassing due to stigmatization of all forms of mental illness. This situation of stigmatization coupled with individuals feeling less inclined to disclose their

---

[14] DSM-IV refers to the fourth edition of the Diagnostic and Statistical Manual of Mental Disorders, which is the standard classification of mental disorders used by mental health professionals.

symptoms may result in underreporting of such cases (Gureje & Lasebikan, 2006). However, the lack of credible statistics and other aforementioned challenges does not imply that this disorder is non-prevalent in Nigeria.

Funk, Drew & Knapp (2012) reported a lopsided ratio in mental disorders among the rich and the poor with the latter being the most affected. Also, Negash *et al*., (2009) find that rural farmers made up nearly half of Bipolar-I disorder patients in Butajira, Ethiopia. Given similar statistics that characterise smallholder farmers in Nigeria *i.e.* being among the poorest and low socioeconomic groups (as reported in Ajibefun, 2002; Asogwa, Umeh & Ihemeje, 2012), there is reason to postulate that a study that concerns BD is well targeted if farmers are chosen as participants to test the study hypothesis.

This study makes use of a modified Bipolar Spectrum Diagnostic Scale (by Ghaemi *et al.,* 2005),[15] (which is effective in addressing the concept of bipolar spectrum and can accurately record subtle features of bipolar illness) in identifying whether farmers within the spectrum of bipolar propensities have different attitudes to risk and uncertainty. It is necessary to point out that this study did not aim to clinically ascertain or identify individuals with BD thus did not in any way provide a categorical response to whether or not an individual has bipolar disorder. Respondents were simply categorised by their scores which were cumulated and matched with the test scoring ranges in which the likelihood of BD propensities increased with a higher score as shown in Appendix 3.

[15] Ronald Pies developed the original scale known as the Bipolar Clinical Scale. Later revised and tested by S. Nassir Ghaemi

2.5 Risk and Uncertainty Attitudes and Participation in Off-farm Income Generating Activities (OFIGA*)

Small farmers especially in low/middle income countries are exposed to numerous uncertainties and risks but have fewer options to cope as formal institutions or policy instruments do not provide commensurate protection. Consequently, their livelihood is vulnerable. Off-farm employment has been documented as a significant risk coping strategy particularly among those with the intent of cushioning production risk (Lamb, 2003) or the risk of income shortfall (Berg (2001); Mishra & Goodwin, (1997)). Although, studies have been carried out with focus on risk and uncertainty attitudes and individual decision making for instance; entrepreneurial decisions (Brockhaus, 1980), acquisitions (Pablo *et al.,* 1996), asset allocation (Riley & Chow, 1992), market behaviours (Fellner & Maciejovsky, 2007), rate of adoption (Just & Zilberman, 1983), farm diversification (Eke-Göransson & Rinman, 2012). However, studies examining the relationship between of risk and uncertainty attitudes and OFIGA participation is limited.

Other studies specific to farming that examines the role of risk and uncertainty attitudes in farm production, investment and management decisions (*e.g.* Backus *et al.,* 1997; Senkondo, 2000; Haneishi *et al.,* 2014 and Brunette *et al.,* 2017) have more often than not reported that risk and uncertainty attitudes have significant effect on various farm decisions. For instance Brunette *et al.,* (2017) find a positive impact of the DM's risk aversion on harvesting decisions, Gong *et al.,* (2016) reported that risk averse farmers where more likely to increase pesticides application. This suggests possible relationship may also exist between risk and uncertainty attitudes on OFIGA participation.

From a different perspective in the literature (see Reardon 1997; Bryceson & Jamal 1997; Chuta & Liedholm 1990), farmers in very poor and developing countries reportedly rely on off-farm activities as a cushion for anticipated risk. Sulewski & Kłoczko-Gajewska, (2014) have found that farmers who plan to engage in off-farm income earning activity may have a slightly higher than average level of risk aversion than those who do not. In contradiction Iqbal, Ping, Abid, Kazmi & Rizwan, (2016) who find that farmers who have earn income off-farm are less risk averse.

According to Islam (1997), it is typical of a risk averse farmer to take the decision to devote some of their productive resources to off-farm activities, with less risk and a more stable income not minding the lower returns from such off-farm farm activities. Mishra & Goodwin (1997), similarly asserts that; for the risk averse farmers', greater farm income variability leads to increased off-farm labour supply. Thus, the opportunity to compensate for the risk and uncertainty related to the variations in farm income is made possible by the off-farm sector. In a similar light, Domingo, Parton, Mullen & Jones (2015) report that progressive farmers are likely to take greater risk in order to achieve greater gains while the conservative will avoid risk. From the various perspectives, one conclusion that stands out is that; for risk averse farmers' off-farm activity is an effective strategy in the reduction of variability, risk and uncertainty.

Risk attitude have also been documented to influence the category of OFIGA chosen by DMs. King (1974) and Musetescu *et al.,* (2007) reported that if the income earning activity is self-owned, the decision maker is more risk seeking. This corroborates Halek & Eisenhauer, (2001) findings of decreased risk aversion among self-employed. Further, Block, Sandner & Spiegel, (2015) that there exists a strong relationship between risk attitudes and the sources of work motivation. They conclude that in terms of *necessity* and *opportunity*, entrepreneurs show risk aversion towards the former and risk tolerance for the latter. Adopting similar approach, farmers could also be categorised into two groups. Farmers that participate in off-farm income activities primarily as a buffer against anticipated farm uncertainties and those that engaged in off-farm income activities because they spotted an investment opportunity.

2.5.1 Determinants of decision to participate in off-farm activity

Although the determinants of participation in off-farm activities have been widely studied (see among others the works of Mduma & Wobet (2005); Bezu *et al.,* (2009) [16], there is limited empirical evidence on the relationship between risk and uncertainty attitudes and decisions to be involved in off-farm income earning

[16] Mduma & Wobet (2005); Bezu et al. (2009) examined the decision to participate and the determinants of activity choice in rural non-farm employment respectively. However, both studies focused mainly on other socioeconomic factors.

activities. In addition, the link between risk and uncertainty attitudes and the type of off-farm activities taken up has not been adequately examined. Ignoring this potentially critical factor can lead to faulty predictions and misleading conclusions hence the relevance of studies which addresses this gap.

As presented in Table 3, factors considered to be determinants of farmers' participation in off-farm activities are (but not limited to) age, gender, education, household size and income. For instance, Man (2009) found age and household size are significant factors influencing decision making in OFIGA among farmers in Malaysia. While OFIGA participation decreased with age, the opposite was the case for household size in several studies. Christopher (2014) findings on farmers in Tanzania regarding household size however was contrary to Man (2009).

Table 3
Selected Studies on Determinants of Off-Farm Participation Decision

Factor	**Authors**	**Country**	**Statistical Models**	**Findings (Effects)**
Farm Size	Rahman (2013)	Bangladesh	Probit	Negative
	Bezabih *et al.* (2010)	Ethiopia	Logit	Positive
Age	Man (2009)	Malaysia	Logit	Negative
Gender	Beyene (2008)	Ethiopia	Probit	Positive
	Bezabih *et al.* (2010)	Ethiopia	Logit	None
Education	Rahman (2013)	Bangladesh	Probit	Negative
	Beyene (2008)	Ethiopia	Probit	None
Household size	Man (2009)	Malaysia	Logit	Positive
	Christopher (2014)	Tanzania	Tobit	Negative
	Raimondi *et al.* (2013)	Italy	Probit	Positive
Access to credit	Shehu & Abubakar (2015)	Nigeria	Probit	Positive
Farm income	Zahonogo (2011)	Burkina Faso	Logit	Negative
Risk & uncertainty attitudes	Sulewski & Kłoczko-Gajewska (2014)	Poland	Descriptive	Positive
Mental health related factors	This thesis	Nigeria	Probit	Mixed*

* Effect depending on the different subjective value function (*i.e.* gain or loss) and conditions (risk or uncertainty)

Bezabih, Gebreegziabher, GebreMedhin & Köhlin (2010) argue that the two main drivers of off-farm involvement decisions are disparities in wages and risk associated with the off-farm option. Of relevance to this study however is the risk factor. Sulewski & Kłoczko-Gajewska (2014) are among the few who have examined off-farm participation as a risk management strategy that is dependent on farmers level of risk aversion. They report that there was difference (though marginally above the average level) in risk aversion between farmers who planned to engage in off-farm income generating activities than farmers who did not. However, Sulewski, & Kłoczko-Gajewska (2014) did not examine uncertainty and estimated 'risk attitude' from simple descriptive statistics. The gap is filled in this thesis using parametric approach and estimating econometric models from which reliable empirical evidence is provided.

2.6 Risk and Uncertainty Elicitation- Lottery-Style Experiments

Lottery-style experiments have featured significantly in studies of both normative and descriptive decision theories. Numerous studies adopting different methods have designed their lotteries payoffs as either real[17], hypothetical or both. It has been argued that using hypothetical payoffs as opposed to real payoff determines the quality of the result (see Kroll & Vogt, 2008). However Kahneman & Tversky, (1979), Irwin, McClelland & Schulze, (1992), Kühberger, Schulte-Mecklenbeck & Perner, (2002), Etchart-Vincent & L'Haridon (2011) suggest that individuals know how they would behave in actual situations and therefore they have no cause to conceal their genuine preferences.

As presented in Table 4, a considerable number of authors have applied, modified or adopted the Ordered Lottery Selection design (OL), Multiple Price List (MPL) design, Becker, Degroot & Marshak (BDM) Design among others in real and hypothetical cases. Notably, researchers have applied lottery type experiments to a wide range of methodologies; and to address different objectives. While Holt and Laury (2002) (HL) employed their lottery approach within the framework of the EUT, Tanaka, Camerer and Nguyen (2010) (TCN) relied on the PT. Other studies such as Bocquého, Jacquet & Reynaud (2014) compared preference from EUT and CPT using both single and mixed domain real payoff lotteries. In the discussion that follows, the merits and demerits of these popular elicitation methods are highlighted.

[17] For real payoffs, the DM at the end of the experiment will be offered some payment reflective of the outcome of the DM's choices during the experiment *e.g.* a DM can earn some physical money; while for hypothetical payoffs the none of the outcomes are real.

Table 4
Selected Popular Lottery Methods of Eliciting Risk and Uncertainty attitudes

Design	**Studies where adopted**	**Lottery type**
The Ordered Lottery Selection (OL) Design	Binswanger (1980)	Real & Hypothetical
	Clarke & Kalani, (2012)	Hypothetical
	Kouamé, (2013)	Real & Hypothetical
	Eckel & Grossman (2002)	Real & Hypothetical
The Multiple Price List (MPL) Design	Holt & Laury (2002)	Real & Hypothetical
	Deck, Lee, Reyes & Rosen (2008)	Real
	Couture, Reynaud, Dury, & Bergez, (2010)	Real & Hypothetical
	De Brauw, & Eozenou, (2014)	Hypothetical
	Clist, D'Exelle, & Verschoor, (2013)	Real
	Reynaud & Couture, (2012).	Hypothetical
Tanaka, Camerer & Nguyen (TCN) Design	Tanaka, Camerer & Nguyen (2010)	Real
	Liu & Huang, (2013)	Hypothetical
	Love, Magnan & Colson, (2014)	Real
	Bocquého, Jacquet & Reynaud (2014)	Real
Becker, Degroot & Marshak (BDM) Design	Becker, Degroot & Marshak (1963)	Real
	Isaac & James, (2000)	Hypothetical
	Harrison, (1989)	Hypothetical
The Random Lottery Pair Design	Hey and Orme (1994)	Hypothetical
	Battalio, Kagel and Jiranyakul (1990)	Real & Hypothetical
	Couture,Reynaud, Dury, & Bergez (2010)	Real & Hypothetical
Mixed Methods	Glöckner & Pachur (2012)	Hypothetical
	Donkers, Melenberg & Van Soest (2001)	Hypothetical
Bespoke methods	Hsee and Weber (1997)	Hypothetical
	Pahlke, Strasser, and Vieider (2015)	Real & Hypothetical

The Ordered Lottery Selection design (OL)

The Ordered Lottery Selection design (OL) by Binswanger (1981) approach shown in Table 5 where a number of 50-50 lotteries are presented to participants from which they are required to pick just one pair to play. While this method is simple and permits parametric estimation, however the potential of deducing risk seeking behaviour is limited. Consequently, this method over-estimates risk aversion. In addition, the 50/50 lottery structure makes it difficult to draw conclusions on warping of probabilities, since identification of warping requires variability in probabilities.

Table 5
Binswanger (1980) version of the OL

Lottery A		Lottery B	
p	₹	*p*	₹
0.5	50	0.5	50
0.5	45	0.5	95
0.5	40	0.5	120
0.5	35	0.5	125
0.5	30	0.5	150
0.5	20	0.5	160
0.5	10	0.5	190
0.5	0	0.5	200

Reprinted from "Attitudes toward risk: Experimental measurement in rural India". Binswanger, H. P. (1980). American journal of Agricultural Economics, 62(3), 395-407.

Multiple Price List (MPL)

In this case the DM has to choose between two lotteries with varying probabilities and fixed payoffs where the expected value of the lottery with the higher variance increases as the experiment progresses. The design of the Multiple Price List (MPL) shown in Table 6 is organised such that a participant is faced with pairs of a given number of lotteries from which the decision maker states preference between each pair (say A and B) for all given paired lotteries. While the payoff of each lottery pair is fixed, the probability however varies. With the onset of the task, the expected value of A is greater than B and the expected value of each pair increases as participants move down each row until it gets to a point where B exceed A. Consequently, the point at which the participants switches determines the risk attitude. This method has been popularised by HL and is applied in numerous studies as it is arguably ease to use. However, results from some studies have shown that the HL-MPL may not be the most suitable method of eliciting risk attitude in developing countries as the multiple switching behaviours have been persistently documented. For example studies carried out in Peru (see Galarza, 2009), Rwanda (see Jacobson & Petrie, 2009) Mozambique (see De Brauw & Eozenou, 2011), South Africa (see Brick *et al.,* 2012), Senegal (see Charness and Viceisza, 2012) each show different rates of inconsistencies among participants who switched choice at least once. Other limitation is that the MPL design leads to systematic framing which coax respondents to pick the lottery on the middle row of the table.

Table 6
Holt & Laury (2002) version of the MPL

Lottery A				Lottery B			
p	€	*p*	€	*p*	€	*p*	€
0.1	2	0.9	1.60	0.1	3.85	0.9	0.10
0.2	2	0.8	1.60	0.2	3.85	0.8	0.10
0.3	2	0.7	1.60	0.3	3.85	0.7	0.10
0.4	2	0.6	1.60	0.4	3.85	0.6	0.10
0.5	2	0.5	1.60	0.5	3.85	0.5	0.10
0.6	2	0.4	1.60	0.6	3.85	0.4	0.10
0.7	2	0.3	1.60	0.7	3.85	0.3	0.10
0.8	2	0.2	1.60	0.8	3.85	0.2	0.10
0.9	2	0.1	1.60	0.9	3.85	0.1	0.10
1	2	0	1.60	1	3.85	0	0.10

Reprinted from "Risk Aversion and Incentive Effects."
Holt, Charles, A., & Susan K. Laury. 2002.
American Economic Review, 92 (5): 1644-1655.

The Becker, Degroot & Marshak (BDM)

The Becker, Degroot & Marshak (BDM) design presented in Table 7 has been applied in both real and hypothetical studies including Becker, Degroot & Marshak (1963), Isaac & James (2000), Harrison, (1989). The BDM is built around bidding where participants' are handed a number of lotteries from which they could only sell if the selling price (S_i) demanded by the participant is equal or less than a randomly picked buying price (C_i) in which case the participant is paid price A_i. On the contrary, where the randomly picked buying price is greater, the participants gets B_i. However, the BDM however depends on the assumptions that participants are expected utility maximizers otherwise, their true certainty equivalents of lotteries will not be disclosed.

Table 7

Becker, Degroot & Marshak (BDM) design

Stages *i*	A_i	B_i	C_i	S_i	$U(s_i)$	Stages *i*	A_i	B_i	C_i	S_i	$U(s_i)$
1	0	100	50	S_1	½	13	S_4	100	50	S_{13}	7/8
2	0	100	75	S_2	¼	14	S_7	S_8	75	S_{14}	43/64
3	0	100	25	S_3	¾	15	S_5	S_4	50	S_{15}	½
4	S_1	100	50	S_4	¾	16	S_9	100	50	S_{16}	13/16
5	0	S_1	50	S_5	¼	17	S_6	S_7	75	S_{17}	7/16
6	S_2	S_3	75	S_6	3/8	18	S_9	S_{13}	50	S_{18}	¾
7	S_2	S_1	25	S_7	5/8	19	S_{11}	S_8	75	S_{19}	5/8
8	100	S_3	25	S_8	13/16	20	0	S_{13}	50	S_{20}	7/16
9	S_5	100	590	S_9	5/8	21	0	S_4	50	S_{21}	5/8
10	S_5	S_1	50	S_{10}	3/8	22	0	S_8	25	S_{22}	¾
11	0	S_3	25	S_{11}	9/6	23	0	S_4	50	S_{23}	3/8
12	S_2	100	75	S_{12}	7/16	24	0	100	75	S_{24}	42/64

Reprinted from "Measuring utility by a single-response sequential method." Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Systems Research and Behavioral Science, 9(3), 226-232.

Bespoke methods

Some studies have employed lottery experiments that do not directly fit in to the categories mentioned above. Hsee & Weber (1997) and Pahlke, Strasser & Vieider (2015) are typical examples. In Hsee & Weber (1997) design, participants were presented with a sure *vs.* 50-50 risky option from which a risk preference index was calculated depending on the participant choice in each group of experiment. Pahlke, Strasser & Vieider (2015) elicitation method features lotteries having a sure amount *vs* a 50-50 risky lottery for seven (7) out of eight (8) pairs; and one in which the lottery consisted of a 50-50 safe option vs a 50-50 option. The demerits of these methods *i.e.* lottery *vs*. sure option is that it does not permit controlling for chances that dissimilarity in complexity of the lottery constitute preference. Also it cannot model many real day-to-day problems.

Overall, the findings from authors who have adopted the lottery style approach to elicit attitudes to risk and uncertainty particularly among the individuals in developing countries leaves fundamental gap for further research particularly as the results from experimental techniques applying such lotteries is contentious on one hand. For example, Reynaud & Couture (2012) in their comparison of Eckel and Grossman *vs*. Holt and Laury report that risk preference measures are affected by the lottery approach used. Similarly, Anderson & Mellor (2009); Ihli, Chiputwa & Musshoff (2013) corroborate this argument by documenting evidence of instability of elicitation methods. Since neither of the approaches is a win-all, this calls for further research in designing and testing alternative lottery-style experiments. On the other hand, these lottery experiments are mostly restricted to monetary payoffs and framed in a way that do not reflect everyday problems.

Non-Lottery based elicitation methods

Besides the stated preference method (such as using lottery experiments as discussed above) which relies on direct elicitation from experiments or questionnaire; other authors' have elicited DMs' attitudes using revealed preference method to examine the relationship between DMs' behaviour in real risky/uncertain scenarios. However this method have been criticised on the issue of external validity.

One of the risk estimation approach that gained popularity in the agricultural economics literature is the Just & Pope (1977, 1978) model based on EUT. This idea behind the model is to examine how output level and output risks are concurrently affected by production inputs. According to Just & Pope (1978), splitting the stochastic production function into mean and variance terms make it possible to isolate the effects of inputs on the mean of output and risk *i.e.* the econometric estimation of the production function relies on aggregating the level and variability of production output thus permitting production inputs to be either risk-increasing or risk-decreasing. Other studies have relied on this model to estimate risk and risk preferences drawing on aversion to variability.

2.7 Summary of Research Gaps Guided by Literature

Although numerous studies have been conducted on risk and a few focusing on uncertainty, this research identified the following gaps based on the literature reviewed in this chapter.

First, studies carried out on risk attitudes of farmers' specifically in developing countries have produced contrasting results – from reports of risk aversion to documentation of risk seeking behaviour. There is evidence that inconsistency in behaviour arises from adopting different theories and employing diverse experimental procedures. Therefore, there is the need for more research on the interaction between contextual or procedural factors and the processes through which individual responses are obtained.

Second, several of the more popular methods adopted in most studies have their respective limitations ranging from the way the experiments are designed which introduces significant cognitive burden; to format and framing that does not adequately reflect everyday problems. In addition, the potential of many leading theories especially non-EU based theories (discussed in Chapter 3) have not been exhaustively examined.

Third, risk and uncertainty attitudes have more often been measured using either the choice list, ranking or allocation procedures. The most popular procedure – the choice list, has relied on binary choices designs in which the outcomes are discrete. There are limited studies that have shown the potential of extending popular theories using continuous binary choices.

Fourth, risk attitudes in proxy decision *i.e.* situations where people make decisions on behalf of others have not been widely researched in Agricultural Economics compared to personal decisions. Crucially, in the literature, findings about whether attitudes in proxy decisions differ from personal decision within the context of risk and uncertainty are mixed. More so only a minute number of studies in this area have been targeted at agriculture in developing countries.

Fifth, there is limited investigation on the possible temporal variability in risk/uncertainty attitudes; and the effect the biological/physiological traits of a decision maker has on these attitudes. Specifically, although mental health related factors are reported to influence decision-making behaviour, yet for the most part economists have not investigated the links between such factors and context specific attitudes towards risk and uncertainty.

Sixth, numerous studies on participation in off-farm activities have focused on other determinants or drivers of the decision to participation in off-farm income earning activities without extending the determinants to accommodate risk and uncertainty attitudes. Currently, there is scarce empirical evidence on risk attitudes and the relationship between the decision to engage in off-farm income earning activities on one hand; and the link between risk attitudes and nature or type of off-farm activity.

Lastly, there is dearth of studies addressing the issues above in developing countries where empirical evidence are much need as farmers risks their livelihoods by being exposed to arguably much larger risks/uncertainties than farmers in developed countries.

Chapter 3

Theories of Risk and Uncertainty– Preference Functional and Decision Rules

3.0 Introduction

Theories that characterize choices under risk and uncertainty are numerous – from normative to descriptive. A considerably large number of authors have introduced, adopted or modified the approach of the Expected Utility theory (Von Neumann & Morgenstern, 1944), the Subjective Expected Utility theory (Savage, 1954) or the Weighted Expected Utility model (Chew & MacCrimmon, 1979; Fishburn, 1983). The non-EU theories that have shaped the agricultural economics literature includes Prospect theory (Kahneman & Tversky, 1979), Rank Dependant Utility theory (Quiggin, 1982), Cumulative Prospect theory (Tversky & Kahneman, 1992), Salience theory (Bordalo *et al.,* 2011) and Regret and Disappointment theories (Bell 1985; Fishburn, 1984; Loomes & Sugden, 1982). In the Chapter, both EU and non-EU theories are reviewed extensively.

Chapter 3 is split into three components namely: EUT, the non-EU theories and other alternative theories. Precisely, section 3.1 is a general review of the EUT, sections 3.2 and 3.3 focuses on non-EU theories, sections 3.4 to 3.8 are expositions of alternative theories including heuristics and decision rules.

3.1 The Expected Utility (EU) model

Expected Utility (EU) Theory (EUT) arguably remains the benchmark theory of decision-making under risk. The earliest record of the EUT dates back to the work of Bernoulli (1738). Broadly, EUT has tended to have two applied versions, one built around the element of wealth or income in which case the DM's utility is a function of disposable income or wealth; and one which does not include initial wealth around which utility is evaluated. According to Cox & Sadiraj, (2002) the expected utility function is linear in probabilities whether decisions are taken under risk or uncertainty and a rational decision maker will choose options that maximize their expected utility.

According to von Neumann-Morgenstern (1944) (VNM hereafter), the EU model can be specified as:

$$\mathrm{EU}(L) = \sum p_i u(x_i) \qquad (3.1.1)$$

or in the case of just two payoffs,

$$\mathrm{EU}(L) = p_1 u(x_1) + (1 - p_1) u(x_2)$$

Where L refers to the probability p_1 of getting payoff x_1 and p_2 of getting payoff x_2 and $u(.)$ is the utility function. Given any two lotteries[18] where $\succ$ represent preference, it is assumed that $L_1 \succ L_2$ if $\mathrm{EU}(L_1) > \mathrm{EU}(L_2)$.

According to von Neumann & Morgenstern (1944) the expected utility of any rational decision maker is derived from four axioms. These axioms are:

Completeness: establishes preference ordering for any comparison of a pair of lotteries. That is a decision maker either prefers one to the other or is indifferent between lotteries (Aumann, 1962).

For any pair of A and B either $A \succcurlyeq B$ or $A \preccurlyeq B$.

Transitivity: implies that a decision maker maintains a consistent preference. If A is preferred to B and B to C; then A is equally preferred to C.

Given A, B and C if $A \succcurlyeq B$ and $B \succcurlyeq C$ then it is expected that $A \succcurlyeq C$.

[18] Lottery in this context is the case in which the outcome is determined by chance

Continuity: Given lotteries A and B then C; and A is preferred to B, B preferred to C then there exists a probability *p* such that B is equally attractive as [A, C; p, (1-p)] thus the decision maker becomes indifferent.

$$A \succcurlyeq B \succcurlyeq C \text{ then } \in p \text{ such that } B \sim [A, C; p, (1-p)]$$

Independence: also known as the *sure-thing principle* states that if each of two lotteries are mixed with a third in the same way, the preference ordering remains independent of the third. That is, given lotteries A and B an agent who prefers A to B also prefers the possibility of A to the possibility of B, wherein the other possibility in both cases is some C.

$$A \succcurlyeq B \text{ then, for all C, } [A, C; p, (1-p)] \succcurlyeq [B, C; p, (1-p)]$$

Any "rational" decision maker ought not to violate these axioms in which case his complete, transitive and continuous preferences can be represented by a utility function

$$u : X \to \mathbb{R}, \text{ where } A \succcurlyeq B \text{ if and only if } U(A) \succcurlyeq U(B).$$

According to the EUT, the shape of the utility function determines the risk attitude. For a concave (convex) utility function, the DM is reported to be risk averse (seeking) while a DM with linear utility function is categorised as risk neutral.

In estimating the utility function, several parametric forms have been widely used in the literature as presented in Table 1 in Chapter 2. Popular among these are the Arrow (1965) and Pratt (1964) Relative Risk Aversion (RRA) and Absolute Risk Aversion (ARA). The ARA provide details regarding the manner in which risk aversion change with different wealth level while RRA show the way risk aversion changes when risky prospect and wealth level are changed by equal proportion.

Assuming a DM having a Bernoulli utility function denoted $U(Y)$ that is twice differentiable, then ARA and RRA is given as equation 3.1.2 and 3.1.3 respectively

$$A(Y) = \frac{-U''(Y)}{U'(Y)} \qquad (3.1.2)$$

$$R(Y) = \frac{-YU''(Y)}{U'(Y)} = YA(Y) \qquad (3.1.3)$$

In constant relative risk aversion (CRRA) utility function the relative risk aversion is assumed to be the same irrespective of wealth level (Y). Here the coefficient of relative risk aversion (γ) is the parameter of interest. The greater the value of γ, the stronger the risk aversion.

For $\gamma = 1$, the utility function of CRRA is given by:

$$U(Y) = log(Y) \qquad (3.1.4)$$

For $\gamma > 0$, the utility function of CRRA takes the form:

$$U(Y) = \frac{Y^{1-\gamma}}{1-\gamma} \qquad (3.1.5)$$

The key characteristics of the specified CRRA are (I) in the event that $\gamma < 1$ the CRRA utility function is increasing in $Y^{1-\gamma}$ and *vice versa* if $\gamma > 1$ (II) whenever $\gamma \rightarrow 1$, the utility function coincides with lnY, (III) $U'''Y > 0$. The popularity of this function arises from the necessity of estimating only a single parameter.

With regards to the constant absolute risk aversion (CARA) utility function, the absolute risk aversion is determined on the supposition that ρ is a positive constant which does not depend of wealth. In this case, adjustments to a DM's preference as risk aversion becomes greater can be estimated subject to a known value of absolute risk aversion.

The utility function of CARA is specified as:

$$U(Y) = -e^{-\rho Y} \qquad (3.1.6)$$

The coefficient of absolute risk aversion $\rho > 0$ implies risk aversion, $\rho = 0$ implies risk neutral and $\rho < 0$ implies risk seeking. One of the main criticisms is that assumption of CARA does not reflect real behaviour as it does not take into consideration any wealth effects.

Other functional forms include the quadratic form also known as the Increasing Absolute Risk Aversion (IARA). For $\rho > 0$, the utility function of IARA takes the form:

$$U(Y) = \mathrm{Y} - \rho Y^2 \qquad (3.1.7)$$

In which case the parameter to be estimated is the coefficient of relative risk aversion (ρ).

One utility function that can accommodate in special cases other utility functions including the CARA and CRRA is the Hyperbolic Absolute Risk-Aversion (HARA). A utility function exhibits HARA in the case where

$$U(Y) = \frac{1-\gamma}{\gamma}\left(\frac{aY}{1-\gamma} + b\right)^{\gamma} \qquad (3.1.8)$$

Where $\gamma \rightarrow -\infty, b > 0$ or $\gamma < 1, b = 0$ then HARA reduces to CARA and CRRA respectively. Unlike CARA and CRRA which permits variation in the magnitude of risk aversion, HARA permits positive or negative slope of the risk aversion measures in addition to variation in the magnitude of risk aversion.

Violations of the axioms of the EUT – Allais paradox (Common Ratio & Consequence)

EUT continues to have support as a theory about how rational decision makers should act. However, it has less support in terms of a descriptive theory of how decision makers act. Empirical evidence have shown that a DM's attitude is inconsistent with the EUT predictions. The axiom that has been criticised most is the independence axiom. The paradoxes of Allais (1953, 1979) provided evidence that an individual decision maker can be inconsistent with EU theory. According to the observations of Allais (1953) preferences are influenced by introducing an independent event into a set of prospects thereby nullifying the validity of the independent axiom. The Allais paradoxes have been categorised as common ratio and common consequence paradoxes (see Levi, 1986; Starmer & Sugden, 1989; Birnbaum, 1999; Cerreia-Vioglio, Dillenberger & Ortoleva, 2013 for details).

Common Ratio Paradox

The paradox is illustrated using the following Allais experiment. An individual is asked to make a choice between the following lotteries:

Lottery 1: Would you prefer A or B?

A:	100% *chance of winning* \$3,000	*B*:	80% *chance of winning* \$4,000
			20% *chance of winning* \$0

Lottery 2: Would you prefer C or D?

C:	25% *chance of winning* \$3,000	*D*:	20% *chance of winning* \$4,000
	75% chance of winning \$0		*80% chance of winning \$0*

Presented with the first set of lottery, most individuals preferred option A to B. However, when presented with the second lottery majority prefer D to C. It is worth mentioning that lottery 1 is reduced by a proportion of 0.25 to obtain lottery 2 however unlike the decision made in lottery 1(where the *sure* option is chosen); the more risky option (D) becomes the most attractive in Lottery 2. This behavior is irrational as for larger probabilities; more weight was attached to the larger of the two while for small probabilities more weight was attached to the smaller of the two.

Common Consequence Paradox

Individuals were presented with lotteries 3 and 4 and were told to make their choices.

Lottery 3: Would you prefer E or F?

E: 100% *chance of winning* \$.5 Million

F: 10% *chance of winning* \$1 Million
89% *chance of winning* \$.5 Million
1% *Chance of winning* \$0

Lottery 4: Would you prefer G or H?

G: 11% *chance of winning* \$.5 Million
89% chance of winning \$0

H: 10% *chance of winning* \$1 Million
90% chance of winning \$0

When presented with such scenario the rational decision maker who prefers E over F in lottery 3 should prefer lottery G over F in 4 implying E $\succ$F and G $\succ$ H. Also given that the expected value of E and F are approximately \$.5 Million, \$.55 Million and G and H are \$.06 Million \$.1Million respectively, judging from this criteria the expected utility maximizer preference should be E $\prec$ F and G $\prec$ H. However, most individuals chose E over F in lottery 3 implying '*risk dislike'* since the "sure" win is chosen. In a contradictory choice pattern, most individuals preferred H to G, which implies '*risk loving'* thus clearly violating the EU axiom. It becomes obvious that when making decisions on the outcome of a "sure" lottery an individual places high value on such lottery as against a case where the payoff have probabilities attached. The common consequence paradox therefore highlights the fact that in certain scenarios people would prefer choices that were earlier rejected. Such case questions the strength and validity of the VNM (1944) EU theory.

Other characteristic of the expected utility function that raises concern among researchers is the linear handling of probabilities. In reality, DMs do not appear to weight probabilities linearly. It has been shown in several studies *(e.g.* Birnbaum, 1999; Wakker, Erev & Weber, 1994; Tuthill & Frechette, 2002 and Neilson, 2001) that the expected utility theory cannot accommodate non-linear probability weighting. This limitation results in the EUT being unable to reflect accurately the behaviour of a decision maker.

3.1.1 Subjective Expected Utility Theory (SEU).

One popular variant of the EUT is Subjective Expected Utility Theory (SEU). The SEU amalgamates the DM utility function and probability distribution. There is difference between the SEU and EUT regarding how probabilities are perceived. As discussed above under the EUT, probabilities are given objective evaluation while the SEU decision maker perceives probability subjectively in situations where there is difficulty defining objective probabilities. The SEU model suggest that DMs act in a manner that suggests they estimate the expected utility of each act then chooses the act assumed to have the highest utility. In other words, prospects and their associated probabilities are given subjective evaluation. Several popular axioms include Savage (1954), Anscombe & Aumann (1963), Machina & Schmeidler (1992) dominate the literature. Economist have often adapted and employed the conceptual and computational composition of the SEU in methodologically examining decision making under uncertainty.

According to Savage (1954), given that $\succcurlyeq$ represents preference relation on F that defines the set of all acts ($f: S \mapsto C$) where S and C are set of states and consequences respectively. Then $\succcurlyeq$ satisfies necessary and sufficient conditions for the representation of the preference relation[19] iff a unique probability measure P that is nonatomic, finitely additive on the set of states S and a cardinally unique utility function $u: C \to \mathbb{R}$ exist such that $\succcurlyeq$ is

$$f \mapsto \int_S u\big(f(s)\big) dP(s) \qquad (3.1.11)$$

This implies that should a rational DM satisfy the axioms; the DM converts any uncertainty regarding the states to a subjective probability measure that represents the DM's belief. In addition, consequences are ordered in a manner corresponding to a utility function that portrays the taste of the DM and acts appraised based on the expected utility criterion. Although the SEU and its axiomatizations are relatively less complicated and intuitive, however like the EUT it also has its shortcomings mostly concerning its descriptive ability. Notably the SEU fails to

[19] These axioms include ordering, sure-thing, independence, comparative probability, non-degeneracy, non-atomicity and dominance. For depth of discussion, see Savage (1954, 1972) and Fishburn (1981).

accommodate uncertainty aversion. An example of this limitation is captured in the popular Ellsberg (1961) paradox.

Violation of Subjective Expected Utility (SEU) – Ellsberg Paradox

The paradoxes of Ellsberg brought to light the fact that DMs prefer events with 'sure' payoffs over those with 'uncertainties' in what Ellsberg (1961) referred to as *ambiguity aversion* (*i.e.* a case where the DM acts like there is no clear-cut objective or subjective belief distribution). An example of Ellsberg (1961) experiment is presented. There are 90 coloured balls in an urn and it is known for sure that the number of red balls is 30. The remaining 60 balls are green and yellow in unknown proportion.

Individuals were required to make a choice between lotteries *A* and *B*

A: *Win $100 if you pick a red ball*

B: *Win $100 if you pick a green ball*

Individuals were required to make a choice between lotteries *C* and *D*

C: *Win $100 if you pick a ball that is not green ball*

D: *Win $100 if you pick a ball that is not red ball*

Most participants choose lottery A over B and D over C which contradicts Savage (1954) sure-thing principle[20] which stipulates, an agent who prefers A to B should also prefers C to D. In lotteries A, given that the DM has information on the proportion of red balls, the DM can then attach probability $^1/_3$ to picking a red ball however in terms of the probability of picking a green ball in lottery B, the much the DM knows is that the probability does not exceed $^2/_3$. Also for lotteries D, the DM is sure of the probability $^2/_3$ of not picking a red ball but the probability of not picking a green ball in lottery C is not known. These situations according to Ellsberg prompt DMs to choose the options with known probabilities over those with uncertainties regarding their probabilities.

[20] Savage stated that if a DM has to choose between two acts A and B, the DM's preferences is determined by the values of the difference in value of acts A, B.

In the light of the above, other decision theories which overcome the limitations of the EU and SEU theories and are poised to accommodate decision-making behaviour uncertainty are reviewed to assess their suitability for this study.

3.2 Rank Dependent Utility model

The Rank dependent Utility (RDU) theory was first introduced in the works of Quiggin (1981, 1982) to accommodate the defects of the EUT with respect to decisions making under risk (Wakker, Erev & Weber, 1994). Rank dependent utility is built on the foundation that the value of an outcome depends both on probability of the outcome and how favourable it appears when ranked with the other possible outcomes (Wakker, Erev & Weber, 1994; Tuthill & Frechette, 2002). According to Quiggin, a DM compares random outcomes based on the DMs' expected utility under probability warping.

For illustration purposes assume that a DM is faced with n-lotteries. Assuming the lottery $L = (x_1; p_1; x_2; p_2; \ldots x_n; p_n)$ generate the consequences x_i with probability $p_{i,}\ i = 1,2 \ldots; n$ where the consequences are ranked $x_1 \geq x_2 \geq \cdots \geq x_n$. The RDEU of lottery L is denoted as:

$$RDU(L) = \sum_{i=1}^{n} \pi_i u(x_i) \qquad (3.2.1)$$

$$\pi_i = w(p_1 + \cdots + p_i) - w(p_1 + \cdots + p_{i-1}) \qquad (3.2.2)$$

π_i denotes decision weights and w is a uniquely determined weighting function.
One distinctive characteristic of the RDU is the non-linear probability weighting function $w: [0,1] \rightarrow [0,1]$ that strictly increases and fulfils the condition $w(0) = 0$ and $w(1) = 1$ (Jindapon & Shaw, 2008; Wakker, 2010). As shown in Diecidue & Wakker, (2001) it is the shape of the uniquely determined weighting function that brings about optimism and pessimism[21] when a DM evaluates a prospect subjectively.

The RDU have proven valuable in explaining the Allais paradox; a well-known violations of EU theory (Segal 1987, Quiggin, 1991). Referring to the lotteries earlier presented in common consequence paradox under the EUT; in the first set of options (A and B) although there is a 10% chance of getting a higher outcome ($1m as compared to a sure $0.5m) most decision makers place more value on the sure payoff rather than gambling to win more (or nothing). However, in the second set

[21] See Section 3.4 for a discussion of these terms

of options (C and D), the individual places more importance on the likely increase in size of payoff (from \$0.5m to \$1m). Since there is no sure-win the DM is prepared to sacrifice a small percentage for the chance to win more. It becomes evident that a percent increase in the probability of getting \$0 in both lotteries is weighed more heavily in the choice between A and B than in the choice between C and D. Thus for large probabilities, more weight is attached to the larger of both while for small probabilities, more weight is attached to the smaller. Kahneman and Tversky (1979) found that judging by the decision weights used by individuals, low probabilities are over-weighted and high probabilities under-weighted.

Given the response obtained in Lottery 1 as discussed in the common ratio paradox presented in section 3.1,

$$\mathrm{A} \succ \mathrm{B} \Rightarrow u(3000) > \pi(0.8)u(4000) \qquad (3.2.3)$$

$$\mathrm{C} \prec \mathrm{D} \Rightarrow \pi(0.25)u(3000) < \pi(0.2)u(4000) \qquad (3.2.4)$$

The violation of VNM expected utility is clearly present as there do not exist any utility function in which both A ≻ B and C ≺ D can hold simultaneously. Assuming the functional form by Tversky & Kahneman (1992) in equation 3.4.7 is adopted *i.e.* $\pi(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{1/\gamma}}$ where $\gamma = 0.61$, the corresponding values are $\pi(0.8) = 0.61$, $\pi(0.25) = 0.29$ and $\pi(0.2) = 0.26$. The respective RDU's for Lotteries A, B, C and D can then reconcile the Allais paradox.

$$\mathrm{RDU_A} = u(3000) = 3000$$

$$\mathrm{RDU_B} = u(0) + \pi(0.8)(u(4000) - u(0)) = 2440$$

$$\mathrm{RDU_C} = u(0) + \pi(0.25)(u(3000) - u(0)) = 870$$

$$\mathrm{RDU_D} = u(0) + \pi(0.2)(u(4000) - u(0)) = 1040 \qquad (3.2.5)$$

This then justify having both A ≻ B and C ≺ D holding simultaneously. For cumulative weighting function (π),

$$\pi(1) - \pi(.8) \geq \pi(.25) - \pi(.20) \qquad (3.2.6)$$

Equation (3.2.6) holds under diminishing sensitivity *i.e.* when the change in probability around 0 or 1 has more impact than similar change in the middle area. Schmeidler (1989) has further extended the RDEU to explain decision under uncertainty.

Notably, the RDU preserves first order stochastic dominance because in appropriate conditions, a rightward shift in the probability distribution mass from one outcome to a strictly higher outcome will leads to a corresponding homogenous shift in the transformed probability distribution (Quiggin 1991; Prigent, 2008). This is made possible since it is the cumulative distribution function that is transformed thus assuring stochastic dominance (Quiggin 1982; Allais 1987; Eide, Von Simson & Strøm 2011, Neilson, 2001). The RDU is closely related to the CEU wherein the RDU is referred to as a special case of the CEU *albeit* for risk. However, the main limitations of the RDU are its inability to accommodate the Ellsberg paradox (detailed in section 3.1) as well as handle mixed domain lotteries among others hence its unsuitability for this study.

3.3 Mean-Standard deviation Theory

Markowitz (1952) paper popularised the mean-variance utility model. The crux of the mean-standard variance (MSD) model is in the measurement of risk by its standard deviation (SD) *i.e.* the presumption that weighted sum of a lottery's EV and SD determines the utility a DM obtains from that lottery. Markowitz (1952) argument is that; in selecting a portfolio an investor aims at maximizing expected return while minimizing the variance. In other words, it is based on the presumption that when a rational DM is presented with risky (or uncertain) choices, he/she selects the payoff with the highest mean (expected value) while simultaneously minimizing variance. It is on this premise that the (static) mean Standard deviation model is built. The model specifies that

$$u(x) = \Omega + \mu(x) - b\sigma(x) \qquad (3.3.1)$$

Where

$u(x)$ = Utility of a prospect x
$\mu(x)$ = Expected value of x
σ = Standard deviation
b = Risk tolerance parameter (*b>0, risk averse and b<0,risk loving)*
Ω = Constant

According to the tenets of mean-variance criterion, when faced with a scenario that involves risk and the DM has to choose between say X and Y the DM should prefer X whenever the expected value of x is greater and variance is smaller than Y. Similarly, the DM should prefer X if the expected value of x is greater even when both have equal variance. In the case where the variance of x is smaller and both have equal expected value, the DM should also choose X. The manner in which risk aversion is estimated in the MSD theory is distinct from that of the EUT. As shown in the equation 3.3.1, risk aversion is the consequence of the penalty foisted on risk. The utility depends on a trade-off between expected value and variance thus the higher the risk parameter b, the greater the risk aversion. The EUT is equivalent to the MSD for an exponential utility function and approximate for quadratic utility function.

The mean variance model[22] has been applied to numerous studies including travel time (Börjesson, Eliasson & Franklin, 2012), portfolio selection (Stone, 1973; Kroll,

[22] This model gained popularity in agricultural economics linear programming literature in the 70's and 80's.

Levy & Rapoport, 1988), movement tasks (Nagengast, Braun & Wolpert, 2011), risk attitude (Mengel, Tsakas & Vostroknutov, 2011). A few studies have attempted to compare the MSD theory with other leading theories. For instance, Nagengast, Braun & Wolpert (2011) test for sensitivity to the variance instead of only the average level of movement and compared the MV model with the CPT and report that their findings favour the MV model. Similarly, Best & Grauer, (2011) paper which focused on examining the behaviour of individuals with extreme risk attitudes under different situations using prospect-theory, power-utility and MV portfolios find that the performance of the MV is superior to prospect-theory. However, De Giorgi & Hens (2009) making similar comparison have reported contrary findings.

Mengel *et al.,* (2016) applied the MV model to estimate risk attitude over monetary and non-monetary outcomes across risk, ambiguity and unawareness however their design was restricted to a fixed versus varying sure outcomes. This thesis however applied the MV model to estimate risk and uncertainty attitudes from a set of non-degenerate prospects.

The main merits of the MV theory are the absence of complication that would otherwise arise from having to estimate several parameters. Also it has the advantage of corresponding to EU maximization under certain conditions. Despite these advantages, there have been many criticisms of the MV model. For instance, its inability to satisfy first order stochastic dominance and accommodate cases of infinite mean/variance. In addition, the MV cannot adequately handle a situation where prospects have equal mean and variance leading to the conclusion of indifference when in actual sense such prospects may not be equally appealing to the DM.

3.4 The Prospect and Cumulative Prospect Models

The prospect theory (PT) proposed by Kahneman & Tversky (1979) caters for the descriptive limitations (including the widely documented Allais paradox) of the VNM expected utility theory. The PT assigns value to gains and losses as opposed to final wealth; and substitutes decision weights for probabilities. In other words, a DM's action pivots on the possible value of losses and gains (instead of the final outcome) which is reference point dependent. According to the proposition of the PT, two steps are involved in the decision making process. A DM first edits and codes the prospect; then proceeds to evaluate it before reaching any decision.

Assuming $\wp = (p_1 x_1, p_2 x_2; 1 - p_1 - p_2 - \mathrm{z})$ represents a prospect which has p_1 probability at x_1, p_2 probability at x_2 and $1 - p_1 - p_2$ at z in which case $\mathrm{x}_1 > \mathrm{x}_1 > \mathrm{z} \geq 0$. Here prospects are appraised by

$$V(p_1, x_1; \dots; p_i, x_i; \dots; p_m, x_m) = \sum_{i=1}^{m} \pi(p_i) v(x_i) \qquad (3.4.1)$$

Where v which represents the function that assigns value to payoffs and π represents decision weights. The original prospect theory recorded its own setbacks both in terms of the way it handled non-additive probabilities and subjective editing operations which results in its violation of first order stochastic dominance[23]. In addition, the specification of the probability weighting function is weak and it poses a challenge when applied to larger results.

The Cumulative Prospect theory thereafter put forward by Tversky & Kahneman (1992) combines the concepts of the rank dependant utility theory and the original prospect theory[24]. The foundation of the CPT primarily relies on the prospect theory paper of Kahneman & Tversky (1979) which was built on two major elements – wherein the cumulative functional are applied separately to gains and losses; and the transformation of probabilities. Kahneman & Tversky (1992) then incorporated

[23] Assuming lottery A for any payoff Y result in a higher probability of a DM getting a payoff equal to or greater than Y under lottery B, then lottery A is regarded as having (first-order) stochastic dominance over B. Details of first and second order stochastic dominance in Appendix 7.

[24] Similar to the prospect theory, the value function however displays reference dependence, diminishing sensitivity and loss aversion (Bui, 2009). However, unlike the PT; the CPT preserves first order stochastic dominance by using cumulative probabilities.

the Rank Dependant Utility theory (RDU) where the objective probability is transformed and the decision weights are determined by the cumulative probabilities. The tenets of the CPT are that DMs judge 'riskiness' of a prospect in relation to a reference point, do not have the same risk attitude for gains and losses and tend to distort cumulative distributions.

Assuming a prospect with probabilities $p_1 \dots p_n$ with outcomes $x_1 \leq \cdots x_m \leq 0 \leq x_{m+1} \leq x_n$. The overall valuation of a prospect $\wp$ is presented as:

$$V(\wp) = \sum_{i=n+1}^{m} v(x_i)\pi_i^{+} + \sum_{j=1}^{n} v(x_i)\pi_i^{-} \qquad (3.4.2)$$

For which v is the value function for payoffs and π^{+} and π^{-} represents decision weights for gains and losses respectively. The value function in Kahneman & Tversky (1992) takes the form of a power function in which responsiveness to gains and losses are distinguished by means of the coefficient[25] (λ). Wherein $\lambda > 1$ suggest that the weight attached to loss exceeds that attached to gain. For the gain and loss domains, the value function specified as in power form is given as:

$$v(x) = \begin{cases} x^{\alpha} & for\ x \geq 0 \\ -\lambda(-x)^{\beta} & for\ x < 0 \end{cases} \qquad (3.4.3)$$

Where the curvature of the value function for gains and that of losses are obtained form the parameters α and β respectively. In conformity with diminishing sensitivity, $0 < \alpha, \beta < 1$ implies concave shape in the gain domain and convex shape in the loss domain. Other value function forms include the exponential form for example in Köbberling & Wakker (2005) and Rieger & Bui (2010) given by:

$$v(x) = \begin{cases} 1 - e^{-\alpha x} & for\ x \geq 0 \\ -\lambda + \lambda \mathrm{e}^{\beta x} & for\ x < 0 \end{cases} \qquad (3.4.4)$$

Or the quadratic value function adopted in Giorgi *et al.,* (2004) and Zakamouline & Koekebakker (2009). The quadratic value function is given by:

[25] In the decision-making literature, lambda (λ) is often known called the coefficient of loss aversion.

$$v(x) = \begin{cases} \lambda\left(x + \frac{\beta}{2}x^2\right), & for\ x<0 \\ x - \frac{\alpha}{2}x^2, & for\ x\geq 0 \end{cases} \tag{3.4.5}$$

The probability weighting function (PWF) of Quiggin (1982) and Kahneman & Tversky (1992) 'combines' probability weighting with EU such that for a prospect ($x_{-n} < 0 < x_m$) with corresponding probabilities (p_{-n}, p_m), the decision weights which are sign-dependent are expressed as

$$\pi_m^+ = w^+(p_m)$$

$$\pi_i^+ = w^+(p_i + \ldots + p_m) - w^+(p_{i+1} + \ldots + p_m) \quad n < i < m$$

$$\pi_1^- = w^-(p_1)$$

$$\pi_j^- = w^-(p_1 + \ldots + p_j) - w^-(p_1 + \ldots + p_{j-1}) \quad 1 < j \leq n \tag{3.4.6}$$

While $w(.)$ is the probability transformation function with characteristic of $w: [0,1] \rightarrow [0,1]$ that strictly increases and fulfils the condition $w^+(0) = w^-(0) = 0$ and $w^+(1) = w^-(1) = 1$. Each segment of the gain and loss equations are forms of the RDU. This implies that the CPT consist of the summation of RDU of p^+ with respect to $\mathcal{W}^+$ and RDU of p^- with respect to the dual of $\mathcal{W}^-$. The curve of the $\mathcal{W}^+$ and $\mathcal{W}^-$ function fitted in Tversky & Kahneman (1992) takes the form of

$$\mathcal{W}^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \quad if\ x \geq 0$$

$$\mathcal{W}^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}} i \quad if\ x < 0 \tag{3.4.7}$$

Where domain sensitivity to differences in probability is represented by the parameters γ for the gain and δ for the loss domain.

Goldstein & Einhorn (1987) suggested a linear-in-log-odds function wherein the parameters that captures separately the curvature (γ^+, γ^-) and elevation (δ^+, δ^-) of the PWF are obtained

$$\mathcal{W}^+(p) = \frac{\delta^+ p^{\gamma^+}}{\delta^+ p^{\gamma^+} + (1-p)^{\gamma^+}}$$
$$\mathcal{W}^-(p) = \frac{\delta^- p^{\gamma^-}}{\delta^- p^{\gamma^-} + (1-p)^{\gamma^-}} \qquad (3.4.8)$$

Smaller values on $\gamma^+$and γ^- translates to reduced sensitivity to changes in probabilities. On the other hand, the parameters δ^+ and δ^- (both > 0) which determine the attractiveness of the prospect suggest that larger (*resp*. smaller) values of δ^+ (δ^-) suggests greater elevation of the PWF for gains (losses). This corresponds to the behaviour reported in the literature as optimism for gains and losses. Another widely applied two-parameter weighting functions in which the probability weighting curvature is distinct from the elevation is Prelec (1998) probability weighting functions (Prelec I and II hereafter).

Prelec II is represented by:

$$\mathcal{W}^+(p) = exp(-\delta^+\left(-\,ln(p_i)\right)^{\gamma^+}) \qquad if\ x \geq 0$$
$$\mathcal{W}^-(p) = \ exp(-\delta^-(-\,ln(p_i))^{\gamma^-}) \qquad if\ x < 0 \qquad (3.4.9)$$

However, Prelec I PWF takes the form of:

$$\mathcal{W}^+(p) = exp(-\left(-\,ln(p_i)\right)^{\gamma^+}) \qquad if\ x \geq 0$$
$$\mathcal{W}^-(p) = \ exp(-(-\,ln(p_i))^{\gamma^-}) \qquad if\ x < 0 \qquad (3.4.10)$$

While the power PWF:

$$\mathcal{W}^+(p) = {p_i}^{\gamma^+} \qquad if\ x \geq 0$$
$$\mathcal{W}^-(p) = {p_i}^{\gamma^-} \qquad if\ x < 0 \qquad (3.4.11)$$

In order to model noise in data, an estimation of outcome sensitivity in the commonly specified in the literature takes the exponential (Luce, 1959) choice form given by:

$$P(V(A), V(B)) = \frac{1}{1 + e^{-\varphi(V(A) - V(B))}} \qquad (3.4.12)$$

where the $P(V(A), V(B))$ specifies the probability that Prospect A will be chosen over B. The parameter φ (response/choice sensitivity parameter) measure arbitrariness in the DM choice while $V(A)$ and $V(B)$ represents the subjective values of the prospects. The closer φ is to zero, the greater the randomness of choices. (For details of different value, weighting and choice functional forms; see Stott (2006) and Balcombe & Fraser (2016)). In summary, the CPT's combination of reference dependence, diminishing sensitivity, perception of loss with respect to gain and non-linear probability weighting distinguishes its predictions with that of the EUT.

Table 8 summarizes the value and probability weighting functional forms and the results obtained from selected literature in which CPT parameters were estimated. These studies estimates various value functions (ranging from power to exponential) and probability weighting functions (including Prelec I & II, Tversky & Kahneman, Goldstein & Einhorn) under different parametric forms. As shown in Table 8, Tanaka *et al.,* (2010) and Toubia *et al.,* (2013) estimated a single parameter PWF, Abdellaoui *et al.,* (2005), Booij *et al.,* (2010) and Bruhin *et al.,* (2010) estimates at least two parameters probability weighting functions. Regarding the shape of the value and PWF, several domain specific CPT studies have reported concave shape in the gain domain and convex shape in the loss domain *i.e.* $0 < \alpha, \beta < 1$ and inverse-s shape PWF $\gamma < 1$. However, studies including Wilcox (2015), Balcombe & Fraser (2015) have reported S-shaped or approaching purely concave or convex PWFs. For detailed estimates of studies that employed different parametric functional in CPT refer to Stott (2006) for Classical and Balcombe & Fraser (2015) for Bayesian approaches.

Table 8

Estimates of utility and probability weighting functions from selected literature

Author(s)	**Findings**						
	α	**β**	**λ**	γ^{+}	γ^{-}	δ^{+}	δ^{-}
	Value function			**Probability weighting function**			
	Power			***Tversky & Kahneman (1992)***			
Tversky & Kahneman (1992)	0.88	0.88	2.25	0.61	0.69		
Wu & Gonzalez (1996)	0.50			0.71			
Harrison & Rutström (2009)	0.71	0.72	1.38	0.91	0.91		
Stott (2006)	0.19			0.96			
				Goldstein & Einhorn (1987)			
Abdellaoui *et al.* (2005)	0.91	0.96		0.83	0.84	0.98	1.35
Stott (2006)	0.19			1.4		0.96	
				Prelec I (1998)			
Tu (2005)	0.68	0.74	3.2	1.00	0.77		
Donkers *et al.* (2001)	0.61	†		0.41	0.41		
				Prelec II(1998)			
Stott (2006)	0.19			1.00		1.00	
Bleichrodt & Pinto (2000)	0.77			0.53		1.08	
Bruhin *et al.* (2010)	0.94	1.14		0.38	0.40	0.93	0.99
Zeisberger *et al.* (2012)	1.00	0.91	1.42	0.86	0.82		
Toubia *et al.* (2013)	0.46	†	1.78	0.53			
	Exponential			***Karmarkar (1979)***			
Abdellaoui *et al.* (2005)	0.09	0.05		0.74			
Booij *et al.* (2010)	0.68	0.83	1.58	0.62	0.59	0.77	1.02
Lobel *et al.* (2017)	0.28	0.09	1.17	0.91			

† indicates $\beta = \alpha$

Notably, while there are observable differences in the estimates in Table 8, the parameters for the gain and loss domains in each of the studies are very similar as regards the shapes of the value and probability weighting function.

Figures A and B below replicates plots of the value functions of Tversky & Kahneman (1992) and Harrison & Rutström (2009) respectively. The value function defined by the deviations from the reference point for the former is steeper than the latter due to the different values of *α, β* and *λ*.

Figures A and *B:* Value functions for different values of α, β and λ defined by deviations from the reference point

Figure A

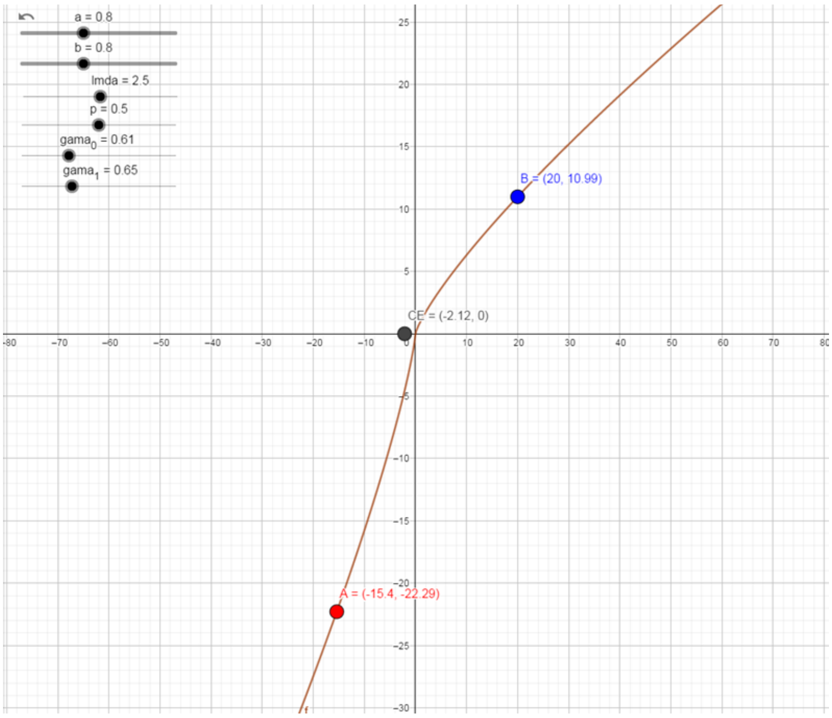
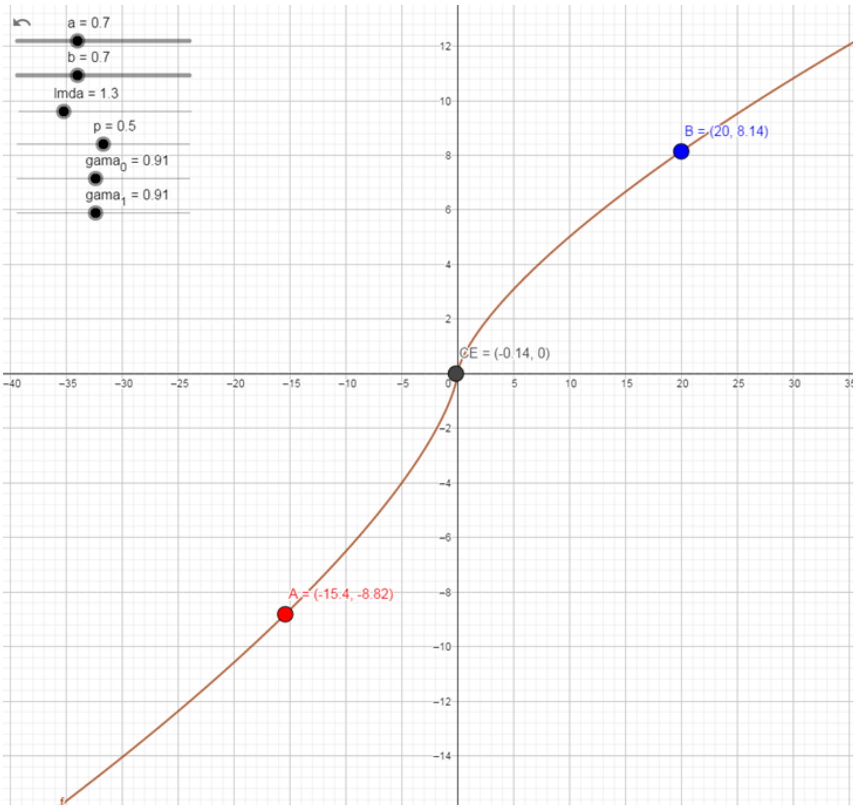


Figure B



3.4.1 CPT for Continuous Distributions

Using CEU under additivity of the discrete subjective probability measures there is a direct correspondence with discrete CPT, and thus under additive continuous densities CEU can be thought of as a generalisation of CPT to continuous densities. This generalisation is discussed in the Section 3.4.2. The CPT as postulated in Tversky & Kahneman (1992) can also handle continuous distribution. For continuous prospects the CPT evaluation takes the form

$$V(x^c) = \int_{-\infty}^{0} \Gamma^{-}[F(x)].\ f(x)v^{-}(x)dx \ + \int_{0}^{\infty} \Gamma^{+}[1 - F(x)].\ f(x)v^{+}(x)dx \tag{3.4.13}$$

Where F and f represents CDF and PDF respectively, $v(.)$ denotes the function that assigns value to outcomes and $\Gamma = \frac{dw(p)}{dp}$.

Recall the PWF function fitted in Tversky & Kahneman (1992) presented in equation *3.4.7* substituted into equation 3.4.13 yields the following:

$$\frac{dw(p)}{dp} = \gamma p^{\gamma-1}[p^{\gamma} + (1-p)^{\gamma}]^{\frac{1}{\gamma}} - p^{\gamma}[p^{\gamma-1} - (1-p)^{\gamma-1}]\,[p^{\gamma} + (1-p)^{\gamma}]^{-\frac{(\gamma+1)}{\gamma}} \tag{3.4.15}$$

There are a number of studies in the literature that have extended CPT to continuous outcome[26] distributions; however it is limited. De Giorgi *et al.* (2004) tested for consistency of the continuous CPT with the Capital Asset Pricing Model, Davies & Satchell (2004) extends binary to continuous prospects with the aim of modelling individual asset allocation, while behavioural portfolio selection under CPT was the centre of attention in the studies of He & Zhou (2011), Pirvu & Schulze (2012) and Jin & Zhou (2008). Also, Davies & Satchell, (2007) examined the level to which a DM's actions contradict the beliefs about his/her risk attitude while Nardon & Pianca, (2014) focused on examining European financial options in the bounds of continuous CPT. Most of these aforementioned works have drawn conclusion that the continuous CPT model generalizes the discrete specification.

[26] See Davies & Satchell (2004) and Connors & Sumalee, (2009) for detailed mathematical derivations.

Form a different approach, Kothiyal, Spinu & Wakker (2011) provides a preference foundation to define the CPT for continuous distributions; Rieger & Wang (2008) appraise the analytical composition of the CPT particularly on conditions encompassing continuous outcome distributions. As a build-up on earlier works, Rieger & Wang (2008) formulated a non-discrete variant of the CPT while retaining its positive properties. Barberis & Huang (2008) examined asset pricing under CPT with particular interest on the probability weighting component while Connors & Sumalee, (2009) and Tian, Huang & Wang (2012) in separate studies within the framework of the CPT examined individual route choice behaviour and risk perception on arrival time respectively in a network whose route travel times is a continuous distribution.

Notably, none of these studies have focused on extending CPT to pairwise continuous outcome primarily with the aim of examining risk and uncertainty attitude using pure monetary 'gambles' across different content domains and targeted at farmers. Closest to this study in some perspective is the paper of Kontek (2009) where the author examined risk behaviour using both discrete and outcome having continuous distributions within gains, loss and mixed domains. The author compares relative utility theory and prospect theory and argues in favour of the former as having descriptive superiority over the CPT.

3.4.2 Choquet Expected Utility (CEU)

Most of the theories in the literature have been targeted at decision making under risk with very few showing potential to accommodate uncertainty. One theory that has been credited for its efficient handling of uncertainty is that of Schmeidler (1982, 1989) and Gilboa (1987) which spearheads Choquet expected utility based studies. According to the CEU theory, a DM behaves as though the utility function is cardinal, holds subjective non-additive beliefs; and estimate the expected utility of each act from which the DM chooses the act assumed to have the greatest expected utility. Thus, the CEU is a special generalization of the EUT that permits the integration of VNM function with regards to non-additive probability measures (Zimper, 2009). The CEU has sufficient and extensive properties to accommodate several preference models including the Subjective Expected Utility and the Maxmin and Maxmax Expected Utility.

The CEU model adequately deals with conditions in which objective probabilities are unknown and the DM *a-priori* is unable to extract subjective probabilities over the state space (Warshawsky-Livne *et al.,* 2012). The Choquet based models has been proven to be flexible and resolve known paradoxes while permitting for distinct discernment of uncertainty from outcome valuation. Chateauneuf, (1994) provided a simple framework which integrates the various axiomizations of CEU independently put forward by Quiggin (1982), Yaari (1987) and Schmeidler (1986, 1989). Unlike EUT which estimates risk via the curvature of the utility function, the Choquet expectation of the utility function is taken with respect to a capacity[27] (in lieu of probability) which is non-additive (Eichberger, Grant & Kelsey, 2010). The work of Chateauneuf, Dana & Tallon (2000) shows the capability of the CEU in handling the DM's preferences in situation of prevalent "ambiguity."

Given a DMs' capacity measure is a function $v : 2^s \rightarrow [0,1]$ that conforms with $v(\emptyset) = 0$, $v(S) = 1$ and $X \subseteq Y \Longrightarrow v(X) \leq v(Y)$for all $X, Y \in 2^s$. Where S represents the finite states of nature, 2^S designates σ-algebra on S respectively; and $s \in S$ the 'state' that s will occur. Then according to the CEU the DM ranks acts f :

[27] A function $[v]$ that allots more weight to event Y than event X when $X \subseteq Y$ is known as a capacity.

$S \rightarrow \mathbb{R}$ under the assumption of a continuous strictly increasing and cardinal utility function $U: \mathbb{R}_{+} \rightarrow \mathbb{R}$. Thus the Choquet expectation of f with respect to a neo-additive capacity v is defined by:

$$\int f dv = \int_{-\infty}^{0} [v(\{s \in S \mid U(f(s)) \geq z\}) - 1] dz + \int_{0}^{\infty} v(\{s \in S \mid U(f(s)) \geq z\}) dz \quad (3.4.16)$$

In estimating the CEU of an act, the DM typically ranks the different states s_i according to their attractiveness that could differ from one prospect to another. The preference of one act over another *say* given two acts a and b follows that a is chosen over b $\left(a \gtrsim b \Leftrightarrow CEU(a, v) \geq CEU(b, v)\right)$ when the CEU of the former is larger compared to the latter.

The distortions of probabilities in the Choquet expected utility normally results in "pessimism" or "optimism" in which case the distortion function v of the former takes a convex shape while for the latter it is concave (Bassett, Koenker & Kordas, 2004). A convex capacity within the context of the CEU is represented by:

$$v(X) + v(Y) \leq v(X \cap Y) + v(X \cup Y) \quad \textit{if for all } \mathrm{X};\ \mathrm{Y} \in 2^{\mathrm{s}}, \quad (3.4.17)$$

While a concave capacity is given by:

$$v(X) + v(Y) \geq v(X \cap Y) + v(X \cup Y) \quad \textit{if for all } \mathrm{X};\ \mathrm{Y} \in 2^{\mathrm{s}}, \quad (3.4.18)$$

This implies that an optimistic DM overweight good outcome while a pessimistic DM overweight bad outcomes.

Although the differences between the CPT and CEU are notable in the separate treatment of gains and losses in CPT and the way capacities are used to calculate decision weights; however the CEU share several similarities with the CPT. The capacities attached to events in the CEU are analogous to the probabilities (with weights attached) in CPT. Crucially, the CPT reduces to a special case of the CEU[28] iff the capacities are additive and preserve first order stochastic dominance. To show that both theories coincide, recall that estimating prospects x_1, X, x_2 within the context of the CEU where $x_1 \geq x_2$, the value of the prospect is

[28] For in-depth discussion, see the papers of Sarin & Wakker (1992, 1994) and Ghirardato & Marinacci (2001). Details on how the CEU under probability warping is computed can be found in Appendix 8.

$$\pi_1 . u(x_1) + \pi_2 . u(x_2) \qquad (3.4.19)$$

Such that the decision weights π_1 and π_2 represented by

$$\pi_1 = v(X) \text{ and } \pi_2 = 1 - v(X) \qquad (3.4.20)$$

are based on how the outcomes are ranked under the assumption of a continuous strictly increasing and cardinal utility function $u: \mathbb{R}_+ \rightarrow \mathbb{R}$. Recall in the case of CPT, the utility function meets condition $u(0) = 0$ and the decision weights are obtained *via* separate weighting function for gains $v^+(.)$ and losses $v^-(.)$. In scenario where the prospect is strictly in the gain domain, $v^+(.)$ takes the place of $v(.)$ in $equation$ (3.4.20) while $v^-(.)$ takes the place of $v(.)$ when the prospect is strictly in the loss domain. However in the case where prospects is in mixed domain the $\pi_1 = v^+(X)$ and $\pi_2 = 1 - v^-(S - X)$. Therefore, if for all events X, the utility function satisfies $u(0) = 0$ under the condition of duality $v^-(X) = 1 - v^+(S - X)$ then CPT reduces to CEU.

The advantages of the CEU that makes it suitable to be adopted for this research includes its significance in handling uncertainty, the thoroughness of its axiomatic foundation, the simple but flexible representations that permits separate discernment of uncertainty/risk from outcomes valuation and most importantly its capability of handling continuous distributions.

3.5 Heuristics and Associated Biases under Uncertainty

Heuristics gained its popularity in psychology possibly from Newell and Simon (1972) application of the word to portray uncomplicated processes that substitute complex algorithms. Heuristics are mental shortcuts often applied to speed up decision-making process. Although these mental processes may be expedient in decision-making where information is imperfect and time is a constraint. Heuristics lower the cognitive burden that abound in decision-making (Shah & Oppenheimer, 2008). It is argued that without applying heuristics in decision-making, simple day-to-day task will result in mental exhaustion if every decision was subjected to deep thinking and evaluations. However, systematic bias and judgement errors have been associated with DMs applying heuristics in decision-making. Several types of heuristics have been described. A selection of the most documented heuristics are discussed as follows.

3.5.1 Representativeness heuristic

According to Tversky & Kahneman (1974), the representativeness heuristic is a case where the DM's judgement of probability is based on stereotypes or similarities. A typical instance is the propensity to use the semblance of a sample as a prediction of the likelihood of an occurrence in the parent population. For instance, when faced with a decision problem say A with limited information, and A shares some attributes of problem B then it is assumed that problems A and B are identical. For example, one might assume that a well-dressed man walking past one's street has a white collar job because it fits one's mental prototype of an individual who works a white collar job. Other biases associated with representativeness heuristic includes underestimating the probability of preceding event recurring termed the '*gamblers illusion*' *e.g.* a favourable outcome is imminent the more the preceding outcomes are unfavourable. On the other hand a DM could cling to the misconception that events with unusual events begets more unusual events.

3.5.2 Availability heuristic

In this case, decision maker evaluates the present based on an experience of the past and make judgment that are dependent on the ease with which an event can be recalled (Tversky & Kahneman, 1973)[29]. As such, a DM becomes inclined to react more to risk in cases where previous occurrence of such risk can be readily called to mind. According to Tversky & Kahneman, (1997) the availability heuristic is often applied under judgement with comparative basis that entails estimating probabilities. For example, if an individual is asked whether the chances of getting malaria in greatest in the April and May, he or she will reflect on experiences over the past years and the response will reflect his or her most recent experience. The consequences of using this heuristics in decision making often result in violating probability rules leading to systematic biases and underestimating or overestimating outcome probabilities. For instance, Kunreuther (1996), reported significant increase in take up of insurance after a natural disaster by DMs that had prior to the event considered it unnecessary.

3.5.3 Anchoring and adjustment heuristic

Anchoring heuristics stems from the propensity of evaluating unknown values and making decision by anchoring on initial point. Research has shown that individuals do make estimates beginning with a starting point and subsequently adjust this starting point to attain the final estimate (Holtgraves & Skeel 1992; Ariyabuddhiphongs, 2011). A typical example is a fish monger who puts a price (usually above the "actual value") on his product with the aim of anchoring the buyer to a high price and haggling downwards until the buyer feels the lower price (in comparison to the higher price) reflects a good bargain.

Some biases have been shown to have links with anchoring heuristics. For instance, DMs can become risk seeking (due to 'overconfidence') after recurrent favourable outcome. Such overconfidence arises from the propensity to set excessively optimistic prediction of uncertain events. Evidence of anchoring and adjustment in lottery task has been documented. For instance, Holtgraves & Skeel (1992) show that in lotteries that had same probabilities of wining; respondents perceived a

[29] The availability heuristic is discussed in-depth in Tversky & Kahneman (1973) paper.

higher probability of winning when the lottery was based on 1/10 compared to 10/100 or 100/1000.

3.5.4 Affect heuristic

The affect heuristics embodies decision-making driven by 'feelings' or 'emotions' with reference to a stimuli such that subjective impressions of 'good' or 'bad' feeling act as heuristics and influences the decisions made by a DM. For instance if a specie of a crop failed in a particular season, a farmer might be unhappy and decide not to cultivate the crop again generalizing the crop as a failure and disregarding statistics which proves otherwise. This implies that the farmer's previous experiences is linked with negative affect that may result in the perceived level of risk being overweighted.

The representations of events in a DM's memory are marked to different extent with affect. During decision-making, DMs depend on the "affect pool" that holds all the good and bad tags intentionally or unintentionally connected with the representations. Some researchers have asserted that more affective reactions to stimuli are more noticeable in situations where a DM lacks time or resources to reflect. Thus, it is typically the foremost reactions, occurring spontaneously then eventually guiding the manner information is processed and decisions made.

Several studies have highlighted the role of heuristics in farm decision making. For instance, Diggs (1991), Rachlinski (2000) and Menapace, Colson & Raffaelli (2012) studies covered issues on heuristics in perception and judgment. These studies found that farmers rely on availability and representative heuristic in evaluation of risks associated with decision-making.

3.6 Decision Rules under Uncertainty

Decision rules are procedures that guides a DM during decision-making particularly when faced with a number of non-stochastically dominated choices under situations in which there may be no possibility to apportion valid estimates of probabilities to the set of payoffs. Two commonly discussed decision rules are the optimist (*e.g.* maximax) and pessimist (*e.g.* minimax) rules popularised by Wald (1985).

3.6.1 Maximax Rule

Using the maximax criterion, the DM assesses decision based on the highest payoff possible. The aim is to maximize the maximum payoff given the DM presumption that for all alternatives, the outcome with the maximum payoff will occur. This rule is referred to as an optimist approach. The sequence of decision involves isolating the maximum payoff of all available options then choosing the option with the highest maximum payoff.

The maximax criterion ($\mathfrak{m}^*$) is defined by

$$\mathfrak{m}^* = \max_{f \in F} \mathfrak{m}_{max}(f)$$

and

$$\mathfrak{m}_{max}(f) = \max_{s \in S} u\big(f(s)\big) \qquad (3.6.1)$$

Where S, F, u represents the state of nature, set of acts and utility function respectively.

For example, a farmer faced with the options of cowpea variety to sow based on the yield in different weather conditions as presented in **Table 9** will pick Cowpea B, which has the highest of the maximum payoff (*i.e.* ₦4000).

Table 9
Hypothetical Decision table

		State of nature (₦/ha)		
		Good	**Average**	**Bad**
Decision alternatives	**Cowpea A**	3000	1500	-1500
	Cowpea B	4000	1750	-2250
	Cowpea C	2000	1000	-1000

Although this criterion has the advantage of being easy to apply, the shortcomings of the maxima rule include the insensitivity to relative differences in outcomes that might adversely affect the decision criteria.

3.6.2 Maximin Rule

In the case of maximin, the DM is most concerned with avoiding the worst possible outcome of the worst-case scenario with the belief that the chance that the worst case in any event will happen is high. Unlike the maximax, the sequence of decision for the maximin DM involves identifying the worst possible outcomes then choosing the option that is best among the worst.
The maximin ($\mathfrak{m}_*$) criterion is defined by

$$\mathfrak{m}_* = \max_{f \in F} \mathfrak{m}_{min}(f)$$

and

$$\mathfrak{m}_{min}(f) = \min_{s \in S} u(f(s)) \qquad (3.6.2)$$

With reference to Table 9, the maximin DM believes that the worst state of nature ("bad yield") will occurs thus the DM will pick Cowpea C which maximizes the minimum outcome (*i.e.* -₦1000). Similar to maximax, one criticism of this criterion for relying on an overly conservative strategy that depends simply on ranking.

Other common decision rules includes the minimax regret and the LaPalace criterion. For the former, the attention is on that states of nature where the DM's minimizes potential regret while considering opportunity that is forgone. The LaPlace-Bayes criterion simply compares prospects based on their averages or mean. For instance, a rational LaPlace-Bayes decision maker will choose option B in Table 10 as its average returns over all three weather conditions is greater than options A and C.

3.7 Regret and Disappointment Theories

These theories are built on the premise that DMs undergo emotions after decision-making. Thus, anticipated emotions are factored into the decision making process which systematically shapes the DM's choice.

The Regret theory is based on the premise that post-decision making, the DM makes comparison of outcomes between the choices made and otherwise if other available alternatives are chosen. With the assumption that the rational DM is characteristically regret averse, regret models are hinged on modifications of the regret-minimax proposition in which case the DMs objective is to minimise their maximum regret by seeking the alternative which results in the least possible regret. The works of Bell, (1985), Fishburn, (1984) and Loomes & Sugden (1982) were at the forefront in the proposition of decision theory of regret which was aimed at justifying decisions taken under uncertainty. According to Loomes & Sugden (1982) the sad (happy) feeling which the DM is feels after finding out that other available options would have yielded a more (less) desirable payoff is termed *regret* (*rejoice*).

There are a number of studies that suggest risk is bi-faceted and is comprised of conventional and regret risk. Thus, a utility function is dependent on prospective payoff and corresponding regret effect (Somasundaram & Diecidue, 2015; Fox, Erner & Walters, 2015). In other words, an individual factors into the utility of the preferred prospect, the feeling that arises thereafter from not obtaining the payoff of other alternative prospect; this element in the decision making process is overlooked by the EUT. This amalgamates elements of minimax and EU theories in the Regret theory.

Assume U constitutes an expected utility representation of preferences and follows the regret theory specification that DMs' aim to optimize expected value. Given that the DM choses a over b then,

$$U(a,b) = u(a) + g\big(u(a) - u(b)\big) \qquad (3.7.1)$$

Where $u(.)$ represents a Bernoulli utility function which satisfies the conditions $u' > 0$ and $u" < 0$; $g: \mathbb{R} \rightarrow \mathbb{R}$ symbolizes the regret function which is determined by the difference in outcome a and b wherein $a > b$ results in disutility.

Whether regret leads to risk aversion or risk seeking has been debated and findings in the literature are mixed. For instance, Josephs, Larrick, Steele & Nisbett (1992); Kardes (1994) Richard, Pligt & Vries (1996) reported that regret increases risk aversion while Bell (1985) findings suggests risk seeking. Interestingly, Zeelenberg *et al.,* (2006) documents both risk averse and seeking behaviours depending on the condition of feedback. Simonson (1992) showed that anticipated regret prompted risk averse-like behaviour in consumers.

From a different perspective Zeelenberg, Beattie, Van der Pligt, & de Vries (1996) found that DMs choices were driven by regret-minimizing rather than risk-minimizing. Zeelenberg & Pieters, (2007) asserted that regret aversion can be clearly distinguished from risk aversion; and both together and separately has an effect on the DM attitude.

The papers of Bell (1985) and Loomes & Sugden (1986) popularised the theory of disappointment that explains a phenomenon wherein a DM experiences a feeling that occurs as a result of the outcome falling short of the DM expectation. The feeling is driven by the preconceived expectation that the best payoff will be achieved within a specific prospect. However, when the outcome is less desirable than anticipated the feeling of disappointment sets in. To determine the extent of disappointment, the expected utility of a lottery serves as its reference point.

For instance, given the states of the world that is a finite set S for which the probability distribution is known prior to the event and a prospect φ is a function $S \rightarrow R$. Assuming the payoff if a DM picks prospect φ and states s occurs, then

$$\varphi(s) = \varepsilon\big(\varphi(s)\big) + \varepsilon[\, d(\varphi(s) - \varepsilon\big(\varphi(s)\big)] \qquad (3.7.2)$$

Where ε>0 represents a constant indicating the extent to which the DM is impacted by a unit of disappointment. $d: R \rightarrow R$ meets the assumptions that: when the expectation of the DM is met, disappointment does not occur *i.e.* $d(0) = 0$, the rise in disappointment is disproportionate to the difference between what occurs and what was expected. If the shape of d is concave on $(-\infty, 0)$, convex on $(0, \infty)$, disappointment looms larger than elation *i.e.* $-d(-x) \geq e(x)$.

Although some studies have used both regret and disappointment interchangeably, Zeelenberg, Van Dijk, Manstead & der Pligt (1998) in line with other studies have reported statistical difference in how these two differ in the manner it is experienced. To distinguish between regret and disappointment, imagine a farmer faced with two prospects A and B as presented in Table 10. Let S_i represents all the possible states of nature the farmer faces. The farmer experiences regret if he or she chooses prospect B and state S_2 occurs (50kg) because the farmer would otherwise have had 100kg had he or she chosen prospect A. On the other hand, if the farmer chooses prospect A and states S_1 (50kg) occurs, he or she experiences disappointment since the outcome is less than S_2 (100kg) even though the outcome of S_1 is as good as the best outcome in prospect B.

Table 10
Hypothetical Payoff table

	States of Nature		
Prospects	**S_1**	**S_2**	**S_3**
A	50kg	100kg	0kg
B	25kg	50kg	25kg

In this case, the difference between regret and disappointment is that the emphasis of the former is comparing across alternative while the latter is within alternatives. This study therefore regards both concepts from these perspectives.

3.8 Salience Theory

The phenomenon "*salience*" according to Taylor and Thompson (1982) refers to information being distorted by the DM as a result of concentrating on the 'most noticeable' region of the outcome thereby resulting in unbalanced weighting of the decision. Salience theory (Bordalo *et al.,* 2012) is designed to model a DM's context-dependent representation of lottery choices under risk where decision weights (warped to the advantage of salient payoffs) substitute objective probabilities. The idea revolves around DMs overweighting of outcomes with large differences, which is modelled via event weighting. In Bordalo *et al.,* (2012) salience is determined through a function which examines the similarities and differences of the characteristic of a lottery in respect of a reference level with the aim of ascertaining the extent to which that characteristic is distinctive and attracts the DM's attention.

Bordalo *et al.,* (2012) expound that given lottery choices dilemma where S represents states of nature for which the likelihood of occurrence p_s of each state $s \in S$ is objective and known *i.e.* $\sum_{s \in S} p_s = 1$ and assume a pair of lottery $\mathcal{L}_1$ and $\mathcal{L}_2$ that result in outcomes of x_s^i and x_s^j in each state s. Given that lottery $\mathcal{L}_i$ are risky; the DM distorts the weights attached to the lottery's greatest salience states in the states of nature S. For lotteries $\mathcal{L}_i$ and $\mathcal{L}_j$ $(i \neq j)$, *the* salience of state s is specified as a bounded continuous function $\sigma(x_s^i$ and $x_s^j)$ that fulfils conditions of:

Ordering: The distance between the lottery payoff x_s^i and its alternative x_s^j determines the salience of state *i.e.* for two states s and $\tilde{s}$ and lotteries i and j, $\sigma(x_s^i, x_s^j) < \sigma(x_{\tilde{s}}^i, x_{\tilde{s}}^j)$ if x_s^{min}, x_s^{max} is a subset of $x_{\tilde{s}}^{min}, x_{\tilde{s}}^{max}$.

Diminishing sensitivity: A uniform increase in the absolute payoff levels across lotteries results in a decline in the salience *i.e.* $\sigma(x_s^i + \epsilon, x_s^j + \epsilon) < \sigma(x_s^i, x_s^j)$ if $x_s^n > 0$ for $n = 1, 2,$ then for $\epsilon = 0$.

Ref*lection:* It is not the payoff domain (gain or loss) that controls salience but rather the size of the payoffs *i.e.* $\sigma(x_s^i, x_s^j) < \sigma(x_{\tilde{s}}^i, x_{\tilde{s}}^j) \Leftrightarrow \sigma(-x_s^i, -x_s^j) < \sigma(-x_{\tilde{s}}^i, -x_{\tilde{s}}^j)$ for any $x_s^n,\ x_{\tilde{s}}^n > 0$.

The salience function is given by equation 3.8.1

$$\sigma(x_s^i, x_s^j) = \frac{|x_s^i - x_s^j|}{|x_s^i| + |x_s^j| + \theta} \qquad (3.8.1)$$

Where $\theta > 0$ modulates salience of states when the payoff of a lottery is zero. A *DM* that is a salient thinker calculates the value of a lottery by

$$V\ (\mathcal{L}_i) = \sum_{s \in S} p_s^i v(\ x_s^i) \qquad (3.8.2)$$

Given that $k_s : k_s\ \in \{1, \dots, |S|\}$ represent the salience ranking of state s for $\mathcal{L}_1$ and chooses lottery $\mathcal{L}_1$ over $\mathcal{L}_2$ iff $\sum_{s \in S} \delta^{k_s} p_s[v(x_s^1) - v(x_s^2)]$. If $\delta < 1$ (*i.e.* the parameter that determines the degree to which salience distorts the weights attached to decisions), the DM chooses $\mathcal{L}_1$ when its payoff is greater than $\mathcal{L}_2$ in the states having the most salience.

Bordalo *et al.,* (2012) salience theory does not rely on the shape of the value function[30] like the CPT. Rather it is dependent on whether the lottery up and downsides are salient *i.e.* a DM is expected to be risk averse and risk seeking for the former and latter respectively. In addition, in salience theory a pair of lotteries from which choice is to be made is not considered independent as with the case of the CPT. For instance, given the lottery choices:

Lottery Choices: Would you prefer A or B?

A:	10% *chance of winning* \$400	B:	10% *chance of winning* \$400
	30% *chance of winning* \$0		30% *chance of winning* \$60
	60% *chance of winning* \$200		60% *chance of winning* \$170

For lotteries A and B, the lowest probability (10%) has the highest possible outcome (\$400). For CPT, lotteries A and B are assumed to be independent thus the DM distorts the small probabilities attached to the high outcome. However, because the outcome of both lotteries are the same (*i.e.* \$400), the salience of the 10% chance of winning \$400 in lottery A *negates* the 10% chance of winning \$400 in lottery B; and the DM choice is not influenced by the likelihood of winning \$400.

Tsetsos, Chater & Usher (2012) concluded that the factors that affect salience are liable to influence the process of decision-making. They further pointed out that in

[30] The authors assume that the value function v is linear.

a typical scenario where the prospect with the largest outcome might be more conspicuous or noticeable, the decision maker may fail to consider the lower outcome on the left section of the tail and as a result may even choose prospects with larger variance. Similarly, Madan, Ludvig & Spetch (2014) and Ludvig, Madan & Spetch (2014) pointed out the propensity of individuals to hold fast to salient events, which could result in memory bias particularly for extreme outcomes and overweighting of similar outcomes in subsequent decisions. This provides evidence of extreme outcome rule wherein the probabilities of the largest gains and losses are overestimated.

Bordalo, Gennaioli & Shleifer (2010) study aimed at explaining the role of salience on local thinking argues that what holds the attention of the individual is the salience of the payoff rather than probabilities. Shleifer, Bordalo & Gennaioli, (2012) and Mersinas, Hartig, Martin & Seltzer (2015) found that the EV or variance does not matter once the payoff of the choices the DM faces are salient or extreme as the focus typically will be on the salient payoff. Chetty, Looney & Kroft (2009) paper on salience and taxation further emphasises the crucial role of salience in consumer reaction to taxation.

According to Dertwinkel-Kalt & Köster (2015), susceptibility to salience can explain deviations from a number from axioms of expected utility theory. Dertwinkel-Kalt & Köster (2015) showed that their extended salience theory can address one of the limitations of the CPT; first order stochastic dominance (FOSD) thereby justifying the argument in the literature that the salience theory is a credible alternative theory. As with several theories however, there are limitations to Salience theory. For instance, since the core of Salience theory is intransitivity, it questions its widespread applicability in economics and finance. In addition, the two-variable function of salience theory results in the theory being overly general.

3.9 Summary

In summary, chapter 3 considered leading theories and models of decision making under risk and uncertainty. This chapter was split into three components namely: EUT, the non-EU theories and alternative theories. Specifically, the chapter covered Expected Utility theory, Mean-Standard deviation theory, Rank Dependant Utility theory, Prospect theory, Cumulative Prospect theory, Salience theory, Regret and Disappointment theories and decision rules and heuristics. The merits and demerits of each theory is highlighted and their application in different scenarios appraised.

As observed from the literature reviewed in this chapter, several of these theories are linked through certain important properties they share. For instance, the EUT being equivalence to the MSD for exponential utility function and approximate for quadratic utility function or the direct correspondence with CPT and CEU under additivity of the discrete subjective probability measures. In addition, the RDU is closely related to the CEU wherein the RDU is referred to as a special case of the CEU albeit for risk. However, they do not coincide in a several aspects such as treatment of reference points, probability transformations, and properties of the value function such as global *vs.* local convexity/concavity. Crucially among these theories, the CPT has received much encomium in decision theory literature as a reliable alternative to many popular theories including the Expected utility theory. In addition, the intuition behind CPT (and equivalent CEU) are credible and can be adapted to several different conditions.

Another key conclusion drawn from this review chapter is that the findings on risk and uncertainty attitudes is influenced by the choice of different theories and methodologies. In addition, although the EUT arguably remains the benchmark theory of decision-making under risk, this theory and several other popular theories have their limitations. Several limitations discussed are addressed by the CPT. Therefore, the CPT is the main theory around which this study is based.

Chapter 4

Research Methods and Models

4.0 Introduction

This chapter covers the conceptual framework and the econometric models and methods used to test hypotheses and achieve the objectives earlier discussed in Chapter 1. To achieve the objective of estimating farmers' attitudes to risk and uncertainty in different context and content domains, this thesis uses both non-parametric methods - relating to the patterns that characterise participant choices and their determinants; and parametric models – based upon CPT as it extends to continuous prospects. Specifically, the Bayesian mixed logit is adopted for this purpose.

The Mean-Standard deviation model is used to estimate the determinants of prospect choice. The objective of examining the effect of bipolar tendencies on risk attitude are determined from estimating multivariate regression while the relationship between risk attitude and decision to engage in off-farm income generating activities are determined from probit and multinomial probit models respectively.

Specifically, Section 4.1 describes the conceptual framework; section 4.2 explains the CPT model, section 4.3 discusses the Bayesian hierarchical model, section 4.4 describes the Mean-Standard deviation model, section 4.5 details the Simultaneous equation model while section 4.6 describes the multinomial probit regression.

4.1 Conceptual Framework

Conceptually the framework for this research pivots on theories of decision-making. The thesis examined the capabilities and extent to which the intuition behind the selected decision-making theories and models corresponds to actual behaviour of DMs' under risk and uncertainty. It also links issues separately examined in previous studies *e.g.* it connects risk/uncertainty attitudes and decision-making behaviour to mental health related factors; and links attitudes to risk and uncertainty obtained from parametric estimation as a determinant of farm decision making in an econometric model. A graphical representation of the framework showing the various components of this study and the hypotheses tested is presented in Figure 1.

Specifically, the hypotheses tested in H_1 and H_2 are whether attitude towards risk and uncertainty depends on content domains. H_3 tests if attitude towards risk depends on context while H_4 tests whether attitudes to risk and uncertainty differ within content domain. H_5 tests if significant differences exist in a DM's risk attitude under personal and proxy context, H_6 whether risk and uncertainty attitude is affected by bipolar disorder and H_7 farmers risk attitude (in the monetary domain) drives decision to engage in off-farm employment

As reported in chapter 2, several findings based on Non-expected Utility theories suggest that individuals are not universally risk-averse *i.e.* risk attitudes often differ across domains. Thus, this thesis tests whether a DM attitude maintains the same attitude in different context and content domains using elicitation methods and experiments detailed in Chapter 5 that differs from previous studies that have tested similar hypothesis.

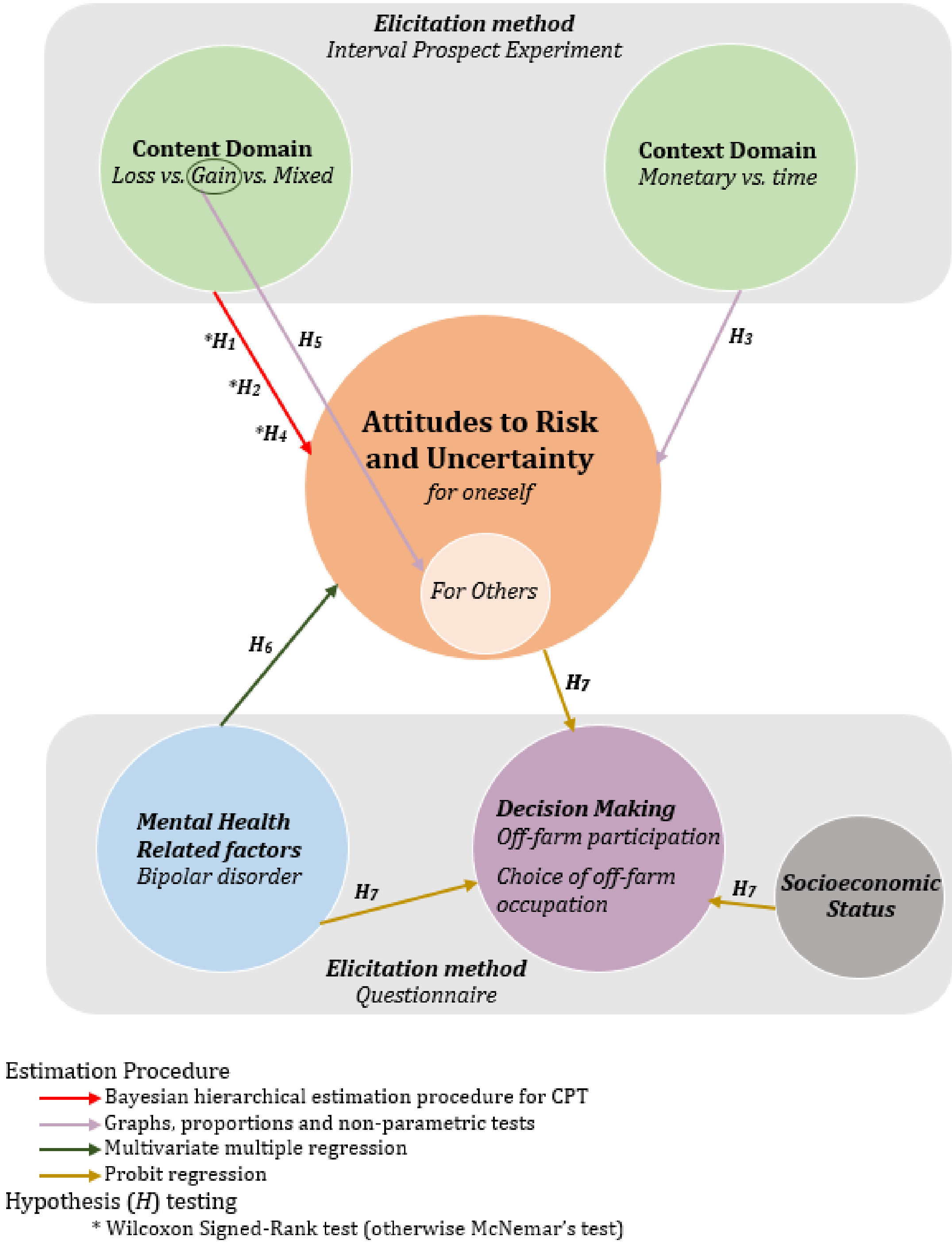


Figure 1. Conceptual Framework

The link between off-farm participation is based on the findings from studies examined in section 2.5, which reported that risk and uncertainty attitude influences farmers' decision-making; and specifically literature which are predominantly based on the models of risk taking behaviour that have examined risk as a determinant of off-farm participation. From this perspective, there is literature that suggest that farmers who engage in off-farm income earning activity may have a slightly higher than average level of risk aversion than those who do not. While a few report that risk attitude has no significant influence off-farm participation decisions. Thus, the proposition tested here is that risk-seeking farmers do not participate in off-farm income activities.

The effects of BD on risk attitude as examined in section 2.4 suggest that individuals with BD tend to 'enjoy' gains more and 'suffer' losses less. Specifically, for an individual at the manic phase, the risk orientation is mostly reported to be risk seeking. Based on the concept that mental health factors influences risk attitude, this study tests the hypothesis that farmers with bipolar disorder are risk and uncertainty seeking.

In summary, the conceptual framework is designed to build on previous studies that examines domain-specific risk and uncertainty attitudes and the decision to participate in off-farm activities separately. This study goes a step further in linking these farm related issues in a single study. Further, it combines researches on bipolar disorder (*e.g.* Yechiam *et al.,* 2008; Martino *et al.,* 2011) with research that has been carried out on risk/uncertainty attitude and decision making.

4.2 CPT & CEU Models

To achieve objectives (i) and (ii) which aims at estimating farmers' attitudes to risk and uncertainty in different context and content domains; the cumulative prospect theory parameters as it extends to continuous prospects is estimated using the Bayesian mixed logit. Drawing from the literature discussed in Chapter 3, the model for this study is built on the CPT and CEU theories. Using Choquet expected utility under additivity of the discrete subjective probability measures there is a direct correspondence with discrete CPT, and thus under additive continuous densities CEU can be thought of as a generalisation of CPT to continuous densities. Thus, in discussing the CPT model hereafter this thesis also implies the equivalent CEU model.

Consider that each farmer is presented with a pair prospects with payoff z_i having probability p_i where $z_i > z_j \Leftrightarrow i > j$ and the probability distribution $f = (z_1, p_1; \dots ; z_n, p_n)$, $z_1 \leq \cdots \leq z_k \leq 0 \leq z_{k+1} \leq \cdots \leq z_n$ stipulates the chances of choosing a prospect. In line with the discussions in Chapter 3, the overall value of a prospect in discrete form is presented as:

$$V = \sum_{i=1}^{k} v(z_i) \left(w^- \left(\sum_{j=1}^{i} p_j \right) - w^- \left(\sum_{j=1}^{i-1} p_j \right) \right) v(z_i)$$

$$+ \sum_{i=k+1}^{n} v(z_i) \left(w^+ \left(\sum_{j=1}^{n} p_j \right) - w^+ \left(\sum_{j=i+1}^{n} p_j \right) \right) v(z_i) \qquad (4.2.1)$$

Given that

$$\pi^+ = w^+ \left(\sum_{j=1}^{n} p_j \right) - w^+ \left(\sum_{j=i+1}^{n} p_j \right)$$

Then expressing the decision weights as

$$\pi^+(z) \equiv w^+\big(1 - F(z)\big) \quad for\ all\ values\ of\ z \geq 0$$

$$\pi^-(z) \equiv w^-\big(F(z)\big) \qquad for\ all\ values\ of\ z < 0 \qquad (4.2.3)$$

From which the continuous CPT form is derived as:

$$V(z^c) = \int_{-\infty}^{0} \Gamma^-[F(z)].\ f(z) v^-(z) dz \ + \int_{0}^{\infty} \Gamma^+[1 - F(z)].\ f(z) v^+(z) dz \qquad (4.2.2)$$

Where F and f represents CDF and PDF respectively, $v(.)$ denotes the function that assigns value to outcomes and $\Gamma = \frac{dw(p)}{dp}$. $w(.)$ is the probability transformation function with characteristic of w: $[0,1] \rightarrow [0,1]$ that strictly increases and satisfies $w^{+}(0) = w^{-}(0) = 0$ and $w^{+}(1) = w^{-}(1) = 1$. The weighting function w^{+} and w^{-} function fitted in this study is Prelec II (Prelec, 1998). The justification for choosing this specification is hinged on its ability to adapt to either inverse S-shaped or S-shaped probability weightings. As presented in Chapter 3, the discrete Prelec II PWF takes the form of:

$$\mathcal{W}^{+}(p) = exp(-\delta^{+}(-\ln(p_i))^{\gamma^{+}}) \quad if\ x \geq 0$$

$$\mathcal{W}^{-}(p) = exp(-\delta^{-}(-\ln(p_i))^{\gamma^{-}}) \quad if\ x < 0 \qquad (4.2.4)$$

However, the continuous Prelec II PWF that is applied in this study takes the form of

$$\Gamma(p) = \frac{\delta^{+}\gamma^{+}}{p}(-\ln p)^{\gamma^{+}-1}e^{-\delta^{+}(-\ln p)^{\gamma^{+}}} \quad if\ x \geq 0$$

$$\Gamma(p) = \frac{\delta^{-}\gamma^{-}}{p}(-\ln p)^{\gamma^{-}-1}e^{-\delta^{-}(-\ln p)^{\gamma^{-}}} \quad if\ x < 0 \qquad (4.2.5)$$

The parameters γ^{+} and γ^{-} determines the curvature of the weighting function while δ^{+} and δ^{-} controls the elevation of the weighting function[31] in the gain and loss domains respectively.

Following with the deterministic form of the CPT, the prospect having the highest subjective value is invariably expected to be chosen by the DM. In reality however this is not always the case, therefore supplementing the deterministic form (which lacks the capacity to produce choice probabilities) with an error theory via choice rule makes it possible to explain stochastic choice of a DM. In line with several studies this study adopts obtaining $f(\,)$ from $P(\,)$ in a pairwise choice

$$f(A|B,\theta) = P(V(A), V(B)) \qquad (4.2.6)$$

Where $f(\,)$ is the probability with which the model predicts choosing prospect A over an alternative prospect B given a set of parameter values θ.

[31] The strength of the s-shaped curve increases with decreasing value of γ. Increasing values of δ on the other hand increases the elevation of the PWF.

For choices between pairs of prospect, the logistic choice function appropriately maps properties of prospects onto choice probabilities (see Stott, 2006). Thus the probability that Prospect A will be chosen over B is determined by

$$P(V(A), V(B)) = \frac{1}{1 + e^{-\varphi(V(A)-V(B))}} \qquad (4.2.7)$$

where the parameter φ (response/choice sensitivity parameter) measure arbitrariness in the DM choice, $V(A)$ and $V(B)$ represents the subjective values of the prospects. The closer φ is to zero, the greater the randomness of choices. Following the recommendations of Stott (2006) and Balcombe & Fraser, (2015) regarding the best combination of value, weighting and choice functions; the estimation of the CPT parameters in this study relies on a combination of value form with power specification, Prelec II weighting function and a logit choice function.

4.3 Bayesian hierarchical parameter estimation

The model estimated in this thesis is hierarchical such that it has parameters that describes the tendencies of each participant on one hand and parameters that accounts for to the distribution of each participants' parameters within a group on the other hand. Thus, the model permits that data from other participants within a group has an effect on parameter estimates for each member participant. This hierarchical estimation is implemented using Bayesian procedure in Python. The choice of hierarchical estimation is to ensure that participants' risk and uncertainty attitudes are not only reliably estimated but maximizes the fit of the data and make the most of its potential in connection with out-of-sample data.

The interpretation accorded probabilities in Bayesian reasoning differs from the frequentists' as probability in the former is interpreted as the degree of belief in the likelihood of an event occurring. This approach also permits for the inclusion of prior knowledge in the estimation of probabilities by applying Bayes' theorem. In Bayesian reasoning, probability distribution is used to quantify the degree of uncertainty and make probability statements about the parameters under the assumptions of fixed data and random unknown parameters.

Assuming the parameter θ and a data set Y having distributions Ɣ and p such that:

$$Y \sim \text{Ɣ}(.|\theta),\ \theta \sim p(\theta) \tag{4.3.1}$$

Under Bayesian rules,

$$p(\theta|Y) = \frac{p(Y|\theta)p(\theta)}{p(Y)} \tag{4.3.2}$$

From the equations above, it becomes possible to calculate the posterior probability distribution $p(\theta|Y)$ for the parameter θ (in lieu a single value for each parameter as with the case of classical models) taking into consideration the data Y from some prior probabilities for the parameter value $p(\theta)$ and the likelihood function $p(Y|\theta)$. Since the marginal likelihood $p(Y)$ only performs a normalizing role, the posterior probability distribution can then be represented as:

$$p(\theta|Y) \propto p(Y|\theta)p(\theta) \tag{4.3.3}$$

Where the marginal likelihood is

$$p(Y) = \int d\theta \, p(Y|\theta)p(\theta) \qquad (4.3.4)$$

Assuming that the data Y is described a model having two parameters θ and ϑ. The hierarchical specification of the joint distribution is given by

$$p(Y|\theta,\vartheta)p(\theta,\vartheta) = p(Y|\theta)p(\theta|\vartheta)p(\vartheta) \qquad (4.3.5)$$

Following Bayesian reasoning, suppose for person j, Y_j represents observations, θ_j constitute parameters at unit level that determines observation Y_j. η represents common parameters with prior density $p(\eta|\vartheta)$ while ϑ is the hyper-parameter that determines the distribution of exchangeable parameters $\theta_1, \ldots, \theta_j$ obtained from a general population; then the stages in the hierarchy corresponds to a sequence of measurements, underlying process and parameter stages.

From the data collected from the experiment described in Chapter 5, $Y_{ij} \;\; j = 1, \ldots, n_i$ are independent given θ_i having a distribution $p(Y|\theta_i)$. There is reasonable basis to suggest the some similarities between the $\theta_i{'}s$. Using a prior distribution where the $\theta_i{'}s$ are considered as samples originating from a common population distribution, the population distribution of the $\theta_i's$ can be estimated.

For Y_j corresponding to all responses by the jth individual, the hierarchical model is given by:

$$Stage\ 1\ (likelihood\ prior):\quad Y_j|\theta_j \sim p\left(Y_j|\theta_j\right)\ for\ j = 1, \ldots, K$$

$$Stage\ 2\ (first\ stage\ prior):\quad \theta_j|\eta \sim p\left(\theta_j|\eta\right)\ for\ j = 1, \ldots, K$$

$$Stage\ 3\ (second\ stage\ prior):\quad \eta \sim p(\eta|\vartheta) \qquad (4.3.6)$$

In which case the posterior distribution is proportional to

$$p(\theta,\vartheta|Y) \propto \; p\left(Y_j|\theta_j\right)p\left(\theta_j|\eta\right) \qquad (4.3.7)$$

With a joint posterior is presented as:

$$p(\theta_1, \ldots, \theta_m, \eta|\vartheta, \ldots, Y_m, \vartheta) \propto \left[\prod\nolimits_j p(Y_j|\theta_j)p(\theta_j|\eta)\right] p(\eta|\vartheta) \quad (4.3.8)$$

Given that θ_j represents arbitrary model parameter of respondent j under k condition.

$$\theta_{jk} = g(\mu_k^\theta + \nu_{jk}^\theta) \quad (4.3.9)$$

Where μ_k^θ and ν_{jk}^θ represent the group average and the deviation of respondent j form the group average. The link function $g(\ )$ maps groups and single contributions on the range of value which determines θ_{jk} is. A logit-link function that allows for a range of parameters between 0 and an upper limit is used. By formulating a Bayesian prior (truncated normal[32]) distribution on the vector of parameters θ, this study simultaneously estimates the parameters for the participants. The prior parameter distributions used in this study draws from studies of similar nature. For instance using Bayesian hierarchical estimation several authors have impose parameter restriction on the CPT parameters. Nilsson, Rieskamp & Wagenmakers, (2011) imposed $0 < \alpha \le 1$; $0 < \beta \le 1$; $0 < \lambda \le \infty$; $0 < \gamma \le 1$; $0 < \delta \le 1$; $0 < \phi \le \infty$. Suter, Pachur & Hertwig, (2013) priors ranged from $0 < \alpha \le 1$; $0 < \gamma \le 1$; $0 < \delta \le 10$; $0 < \varphi \le 10$. Similarly, Broomell & Bhatia (2014) priors ranged from $0 < \alpha \le 1$; $1 < \lambda \le 10$; $0 < \gamma \le 1$; $0 < \varphi \le 1$. Parameter ranges in other studies include Toubia, Johnson, Evgeniou & Delquié, (2013) $0.05 \le \alpha \le 2$; $\lambda \le 10$; $0.05 \le \gamma \le 2$; Haffke & Hübner, (2014) $0 < \alpha \le 1$, $0 < \gamma \le 1.5$, $0 < \delta \le 4$, and $0 < \varphi \le 10$ and Glöckner & Pachur (2012) that restricted their parameter values to $0 < \alpha \le 1$, $0 < \lambda \le 10$, $0 < \gamma \le 1$, $0 < \delta \le 4$, $0 < \varphi \le 10$. This thesis adopts $0.05 \le \alpha \le 2$; $0.05 \le \beta \le 2$; $0.05 \le \lambda \le 3$; $0.25 \le \gamma \le 2$; $0.25 \le \delta \le 2$; $0 < \phi \le \infty$. Since the version of CPT in this study is sign-dependent, a vector of 8 parameters (α, β, λ, γ^+, γ^-, δ^+, δ^-, φ) is estimated. Implying that the entire vector of unknown parameters at group-level is given by:

$$\theta = \mu_\alpha, \mu_\beta, \mu_\lambda, \mu_\gamma, \mu_\delta, \sigma_\alpha, \sigma_\beta, \sigma_\lambda, \sigma_\gamma, \sigma_\delta, \sigma_\varphi \quad (4.3.10)$$

[32] The truncated normal distribution in this case refers restriction of the upper and lower domains to specific range of values.

This methodology adopted in this study follows two steps. First, in line with Nilsson *et al.,* (2011), individual parameters are obtained from independent group-level with logarithm having a normal distributions represented as;

$$\alpha_j \sim N(\mu_\alpha, \sigma_\alpha);\ \ \beta_j \sim N(\mu_\beta, \sigma_\beta);\ \lambda_j \sim N(\mu_\lambda, \sigma_\lambda);\ \gamma_j \sim N(\mu_\gamma, \sigma_\gamma);\ \delta_j \sim N(\mu_\delta, \sigma_\delta);\ \varphi_j \sim N(\mu_\varphi, \sigma_\varphi) \tag{4.3.11}$$

As regards the group means a standard normal priors is used. The link function specified in equation (4.3.9) ensure that transformation result in prior values that are uniformly distributed between the lower and the upper boundaries. The next step involves the derivation of the posterior distribution of the CPT parameters using Markov Chain Monte Carlo (MCMC) algorithms that make it possible to approximate the posterior distribution within the context of Bayes' theorem. The number of iterations, burn-ins and retained posterior draws are reported in section 7.1 of Chapter 7.

Overall, given that some relationships are complex to model, a flexible model like the Bayesian hierarchical models can be very reliable. In addition, considering that any differences across and similarities between individuals are at the same time accommodated in hierarchical models, it is capable of addressing the shortcomings of the estimates derived from averaging data or participant level parameter estimation. According to Nilsson *et al.,* (2011) and Steyvers & Lee, (2006), hierarchical models recognises that while individuals may differ, they may also share some similarities; thus each single DM’s parameter estimate in a model is believed to have meaningful dependencies on others included in that model.

4.4 Generalized Estimating Equations (GEE) Method

In order to examine the association between the choices made by subjects, the magnitude of the prospect (in terms of mean and variance) and domain of the prospects; this study uses the Generalized Estimating Equations (GEE) (popularised by Liang & Zeger, 1986 and Zeger & Liang, 1986). Liang & Zeger (1986) applied the GEEs as an extension of the generalized linear model that could accommodate within-subject or within-cluster correlation while producing estimates that are reliable and results that are robust. The GEE suits the data analysed in this study for the reasons that there may be tendency that the participants' choice of prospect per task have same correlation across observation thereby contravening the independence assumptions upon which other regression models are built. Crucially, the goal is to reveal differences in the population average response.

Assuming there exist some correlation between (and independence across) responses from participants; we then estimate a model where the dependent variable Y_{ij} indexes the ith response ($i = 1, 2, \dots, n_i$) for the jth participant $j(j = 1, 2, \dots, K)$ with a response vector of $Y_j = (y_{j1}, \dots; y_{jk})'$, the mean vector denoted by $\mu_j = (\mu_{j1}, \dots; \mu_{jk})'$ and corresponding covariates $X_j = (x_{j1}, \dots; x_{jk})'$. The assumptions of the marginal regression approach of GEE are that the expected value take the form of $E(Y_{ij}|x_{ij}) = \mu_{ij}$ and variance $Var(Y_{ij}|x_{ij}) = \phi v(\mu_{ij})$. The relationship that exists between the covariates and the marginal mean is determined the function:

$$g(\mu_{ij}) = x'_{ij}\mathcal{B} \qquad (4.4.3)$$

Where the probit link $g(\mu_{ij}) = \Phi^{-1}(\mu_{ij})$ with a variance of $v(\mu_{ij}) = \mu_{ij}(1 - \mu_{ij})$ and $\phi = 1$. $g, v, \phi,$ and Φ represents the link function, variance function, dispersion parameter and inverse standard normal cumulative distribution function respectively.

The estimation of ϱ parameter is necessary towards obtaining estimates of GEE. Thus for the jth farmer, the specification of the working variance–covariance matrix for Y_j is:

$$V_j \; = \; \phi A_j^{\frac{1}{2}} R_j(\alpha) A_j^{\frac{1}{2}} \qquad (4.4.4)$$

where $A_j$and $R_j(\varrho)$ represents n x n diagonal and working correlation matrices defined by the vector of parameters α respectively The regression parameter β in the GEE model is determined by solving the equation:

$$\omega(\beta) \equiv \sum_{j=1}^{N} \frac{\partial \mu_i(\mathcal{B})}{\partial \mathcal{B}'} [V(\hat{\varrho})]^{-1} \left(y_j - \mu_j\right) = 0 \qquad (4.4.5)$$

The working correlation assumed for the data type is an exchangeable correlation structure $Corr\,(Y_{ij}\,, Y_{jk}) = \varrho$ implying that the jth person has matching α correlation at each estimation point.

The GEE model estimated in this study examines the effect of the mean ($\mathcal{B}_1$) and standard deviation ($\mathcal{B}_2$) of the prospect outcomes on the probability of participants j choosing the outer prospect (Y) while controlling for prospects (lottery) design[33] ($\mathcal{B}_3$ to $\mathcal{B}_{11}$). The estimation model specification is:

$$\begin{aligned} Y_j(1 = if\ the\ jth\ participant\ prefer\ the\ outer\ ('risky')\ prospect) \\ = \mathcal{B}_0 + \mathcal{B}_1 Mean + \mathcal{B}_2 Std + \mathcal{B}_3 gain * SD + \mathcal{B}_4 loss * Std + \mathcal{B}_5 gain \\ + \mathcal{B}_6 loss + \mathcal{B}_7 mixed + \mathcal{B}_8 zerobound\_outer\_gain \\ + \mathcal{B}_9 zerobound\_outer\_loss + \mathcal{B}_{10}\ lower\_zerobound\_inner\_mixed \\ + \mathcal{B}_{11}\ upper\_zerobound\_inner\_mixed \qquad (4.4.6) \end{aligned}$$

Where,

$\boldsymbol{Mean} = Difference\ in\ mean\ between\ the\ payoffs\ of\ prospects\ A\ and\ B$

$\boldsymbol{SD} = Difference\ in\ standard\ between\ payoffs\ of\ prospects\ A\ and\ B$

$\boldsymbol{gain} = 1\ if\ payoffs\ are\ strictly\ positive\ domain$

$\boldsymbol{loss} = 1\ if\ payoffs\ are\ strictly\ negative\ domain$

$\boldsymbol{mixed} = 1\ if\ payoffs\ cut\ across\ gain\ and\ loss\ domains$

$\boldsymbol{zerobound\_outer\_gain}$

$= 1\ if\ gain\ task, lower\ limit\ of\ outer\ prospect\ bound\ at\ zero$

$\boldsymbol{zerobound\_outer\_loss}$

$= 1\ if\ loss\ task, upper\ limit\ of\ outer\ prospect\ bound\ at\ zero$

[33] The design referred to in this section is presented in Figure 3 and discussed in details in Chapter 5.

$\boldsymbol{lower\_zerobound\_inner\_mixed}$

$$= 1\ if\ mixed, lower\ limit\ of\ inner\ prospect\ bound\ at\ zero$$

$\boldsymbol{upper\_zerobound\_inner\_mixed}$

$$= 1\ if\ mixed, upper\ limit\ of\ inner\ prospect\ bound\ at\ zero$$

Recall that the justification for the estimation model is based on the proposition of M-SD. When faced with a risk/uncertain scenario the DM should prefer B whenever: the expected value of B is greater and SD is smaller than a; the expected value of B is greater even when A and B both have equal SD; and (or) the variance of B is smaller even when both have equal expected value. The preference for standard deviation over variance in this specific model is to ensure uniform units of both EV and SD.

4.5 Probit Model

In order to achieve objective (v) which is to investigate the relationship between risk and uncertainty attitudes and decision to engage in off-farm income generating activities (OFIGA), a probit model parameters is estimated. As a special case of the Generalised Linear Model, the probit model (Bliss, 1934; Fisher, 1935) is a non-linear probability econometric model suitable for fitting binary response model by defining a function $f(*)$ using the cumulative distribution function of the standard normal distribution. The elicitation of the probability Pr of choosing to participate in OFIGA is performed as follows. Let y_j represent a random variable with Bernoulli distribution having probability

$$\begin{aligned} Pr(y_j = 1|x) &= Pr(y_j^* > 0|x) \\ &= Pr(x_j'\mathcal{B} + \varepsilon_j > 0|x) \\ &= Pr(\varepsilon_j - x_j'\mathcal{B}|x) \qquad (4.5.1) \end{aligned}$$

Given the assumptions of independently and normally distributed error
$\varepsilon_i \sim i.i.d.N(0,1)$

$$\begin{aligned} Pr(y_j = 1|x) &= 1 - \Phi\left(-\frac{x_j'\mathcal{B}}{\sigma}\right), \sigma \equiv 1 \\ &= \Phi(x_j'\mathcal{B}) \qquad (4.5.2) \end{aligned}$$

Φ represents the standard normal CDF and β denotes $kx1$ vector of coefficient
Consider the regression model,

$$y_j^* = X_j'\mathcal{B} + \varepsilon_j$$

$$y_j = \begin{cases} 1 & if\ y_j^* > 0 \\ 0 & otherwise \end{cases} \qquad (4.5.3)$$

Where y_j^* in the case of this study represents farmers' choice regarding participation in off-farm income generating activities, the vectors of explanatory variables (described in Table 11) are denoted by X_j; $\mathcal{B}$ is the model coefficients representing the magnitude of the explanatory variables.

Let x denote $kx1$ vector of output and $Nx1$ vector of input represented by y; the product of the likelihoods of the individual observations results in the likelihood of the whole sample because observations are independent and identically distributed.

$$f(y|x,\mathcal{B}) = \prod \Phi(x_j'\mathcal{B})^{y_j}\,[1-\Phi(x_j'\mathcal{B})]^{(1-y_j)}$$

$$f(y|x,\mathcal{B}) = \prod \Phi_j^{y_j}(1-\Phi_i)^{1-y_j} \qquad (4.5.4)$$

The Log likelihood function is given by:

$$lnL = \sum_j y_j\, ln\, \Phi_i + (1-y_j)\, ln(1-\Phi_j) \qquad (4.5.5)$$

To obtain the average marginal effect for a continuous variable assuming other variables are kept at a constant $Pr(Y = 1|X = x)$:

$$\frac{\partial Pr}{\partial x_j} = \frac{1}{n}\sum_{j=1}^{n} \Phi(x_j'\mathcal{B})\mathcal{B} \qquad (4.5.6)$$

Or discrete for the effect of a change on the probability P(Y = 1|X = x):

$$\frac{\partial Pr}{\partial x_j} = \frac{1}{n}\sum_{j=1}^{n} [\Phi(x_j'\mathcal{B}|x_j^k = 1) - \Phi(x_j'\mathcal{B}|x_j^k = 0)] \qquad (4.5.7)$$

While the marginal effect at means for a continuous variable and discrete variables respectively is derived by:

$$\frac{\partial Pr}{\partial x_j} = \Phi(\overline{x_j'}\mathcal{B})\mathcal{B}$$

$$\frac{\partial Pr}{\partial x_i} = \Phi(\overline{x_j'}\mathcal{B}|x_j^k = 1) - \Phi(\overline{x_j'}\mathcal{B}|x_j^k = 0)] \qquad (4.5.8)$$

The independent variables and their expected signs drawing from earlier studies discussed in Chapter 2 are presented in Table 11. *A-priori* it is expected that age, gender, farm size and ownership of farm have a negative effect on OFIGA while marital status, education and farm hours either have a positive or negative relationship with OFIGA. As for the relationship between risk and uncertainty attitudes variables and OFIGA, the expectation was a negative relationship exist between α, γ^{+} and OFIGA.

Table 11

Definition of Variables subjected to Probit and multinomial Probit Regression Models

Variable ID	Description	Expected Sign
Dependent		
Y_j	1= Farmer engages in off-farm income generating activities, 0=otherwise	
Independent		
α	Numerical value (Lower values = greater risk aversion for gains)	-
δ^+	Numerical value (Lower values = higher pessimism for gains)	-/+
γ^+	Numerical value (Lower values = inverse *S*-shape)	-/+
β	Numerical value (Lower values = greater risk seeking for losses)	+
δ^-	Numerical value (Lower values = higher optimism for losses)	-/+
γ^-	Numerical value (Lower values = inverse *S*-shape)	-/+
Age	Number of years	-
Gender	1 male , 0 otherwise	-/+
Marital Status	1 married , 0 otherwise	-/+
Household size	Number living in a farm household	
No Education	1 no formal education, 0 otherwise(Reference)	-
Primary Edu.	1 primary education, 0 otherwise	+
Secondary Edu.	1 secondary education, 0 otherwise	+
Tertiary Edu.	1 tertiary education, 0 otherwise	+
Farm size	Number of hectare	-
Farmtenure	1 farm owner, 0 otherwise	-
Farmtype	1 one cycle, 0 otherwise	+
Farmhours	Number of hours spent on farm/day	-
Location	1 Rural, 0 otherwise	-
Cooperatives	1 member, 0 otherwise	-/+

Given the variables defined in Table 11 that are guided by the relationships identified from literature and discussed in section 2.5 in Chapter 2, the probit model estimated in this study examines the effect of risk and uncertainty attitudes and socioeconomic characteristics on the probability of farmers' participation in OFIGA (Y_i). This relationship is tested through estimating the specified probit model parameters (4.5.9) using the Maximum Likelihood Estimation (MLE) technique in Python software.

$$
\begin{aligned}
Y_j(1 = if\ the\ jth\ participant\ engages\ in\ OFIGA, 0\ otherwise)\\
= \mathcal{B}_0 + \mathcal{B}_1\alpha + \mathcal{B}_2\delta^{+} + \mathcal{B}_3\gamma^{+} + \mathcal{B}_4\beta + \mathcal{B}_5\delta^{-} + \mathcal{B}_6\gamma^{-} + \mathcal{B}_7 age\\
+ \mathcal{B}_8\, gender + \mathcal{B}_9\, mstatus + \mathcal{B}_{10}\, priedu + \mathcal{B}_{11}\, secedu\\
+ \mathcal{B}_{12}\, higheredu + \mathcal{B}_{13} hhsize + \mathcal{B}_{14} farmsize + \mathcal{B}_{15} farmhours\\
+ \mathcal{B}_{16}\, farmtenure + \mathcal{B}_{17} farmtype + \mathcal{B}_{18} cooperative\\
+ \mathcal{B}_{19} location\\
+ \mathcal{B}_{20} rural \qquad (4.5.9)
\end{aligned}
$$

Five (5) models were estimated to determine the effect of selected variables on OFIGA participation. Model I estimated the effect of bipolar tendencies alone on OFIGA participation, Model II estimated the effect of risk attitudes on OFIGA participation while Model III incorporates bipolar tendencies, risk attitudes and socioeconomic characteristics in the estimation. Models IV and V are similar to Model III and IV respectively but for uncertainty.

4.5.1 Multinomial Probit Estimation

In order to identify the determinants of preference for the type of off-farm income generating activities, this thesis employs the Multinomial Probit estimation (MNP hereafter). The OFIGA types which make up the dependent variable are categorised into worker, self-employed and employee with No-OFIGA participation as the base outcome $i.e.\ i = 0, 1, 2, 3$ where $0 = No\ OFIGA$, $1 = Self\_employed$, $2 = worker$ and $3 = paid\ employment$ as such a farmer j engages in an OFIGA i ($i \in N$). Assuming the farmer seeks to maximize utility on the types of OFIGA, U_{ij} is determined by the farmers' characteristics $\mathcal{B}'X_{ij}$ as well as random error ε_{ij} presented as:

$$U_{ij} = \mathcal{B}'X_{ij} + \varepsilon_{ij} \sim N[0, \Sigma] \qquad (4.5.10)$$

Thus the choice of OFIGA i that maximizes the utility of the jth farmer is:

$$U^{*}(\psi) = U[\kappa_b(\psi)\kappa_c(\psi)] \qquad (4.5.11)$$

Where ψ, κ_b, κ_c represents the farmers' characteristics, the base outcome occupation (No OFIGA) and the set of OFIGA alternatives. Thus, the probability of choosing OFIGA i by the jth farmer is:

$$P(OFIGA = i|\, \mathcal{B}, X_{ik}, \Sigma^{*}) = \int_{-\infty}^{\mathcal{B}^{*}X_1^{*}} \dots \int_{-\infty}^{\mathcal{B}^{*}X_{i-1}^{*}} f(\varepsilon_{i1,\dots,}^{*}\varepsilon_{ji-1}^{*})\partial\varepsilon_{i1,\dots,}^{*}\partial\varepsilon_{ji-1}^{*} \qquad (4.5.12)$$

In which case the PDF of the multivariate normal distribution is obtained from $f(.)$ under the assumption that the random error $N[0, \Sigma]$ having a covariance matrix

$$\sum = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{12} & \sigma_2^2 & & \vdots \\ \vdots & & \ddots & \\ \sigma_{1n} & \cdots & & \sigma_n^2 \end{pmatrix}$$

Thus, the model estimating the determinants of preference for the types of off-farm income generating activities is presented as:

$$\begin{aligned} Y_j(1 = if\ the\ jth\ farmer\ is\ selfemployed, 2 = worker, 3 = takes\ paid\ work) \\ = \mathcal{B}_0 + \mathcal{B}_1\alpha + \mathcal{B}_2\delta^+ + \mathcal{B}_3\gamma^+ + \mathcal{B}_4\beta + \mathcal{B}_5\delta^- + \mathcal{B}_6\gamma^- + \mathcal{B}_7 age \\ + \mathcal{B}_8\, gender + \mathcal{B}_9\, mstatus + \mathcal{B}_{10}\, priedu + \mathcal{B}_{11}\, secedu \\ + \mathcal{B}_{12}\, higheredu + \mathcal{B}_{13} hhsize + \mathcal{B}_{14} farmsize + \mathcal{B}_{15} farmhours \\ + \mathcal{B}_{16}\, farmtenure + \mathcal{B}_{17} farmtype + \mathcal{B}_{18} cooperative \\ + \mathcal{B}_{19} location \\ + \mathcal{B}_{20} rural \end{aligned} \tag{4.5.13}$$

The socio-economic and risk/uncertainty variables are defined in Table 11 above**.** Similar to the probit model, five (5) models estimated using python were used to determine the effect of selected variables on the types of OFIGA engaged in by farmers. Model I estimated the effect of bipolar tendencies alone on types of OFIGA, Model II estimated the effect of risk attitudes on types of OFIGA engaged in while Model III incorporates bipolar tendencies, risk attitudes and socioeconomic characteristics in the estimation. Models IV and V are similar to Model III and IV respectively but for uncertainty.

4.6 Multivariate Multiple Regression

The objective of examining the effect of bipolar tendencies on risk attitude are determined from estimating a multivariate regression model. This model was chosen because there was the need to predict multiple response variables determined by more than two independent variables taken into consideration simultaneously. In addition, unlike the ordinary least square regression the multivariate multiple regression has the advantage of allowing tests of the coefficients across the different response variables to be carried out.

Recall from section 4.3 that the farmer risk and uncertainty attitude CPT parameters $(\alpha, \beta, \lambda\,, \gamma^{+}, \gamma,^{-}\,\delta^{+}, \delta^{-}, \varphi)$ is determined by the farmers' mental health related factors (bipolar disorder and mood) and other farmer specific characteristics. Thus, in general form the multivariate multiple regression model is specified as

$$Y = \mathcal{B}^{T} X \qquad 4.6.1$$

Where

Y = row vector of 8 CPT parameters

X = row vector of bipolar disorder, mood and other farmer specific characteristics

$\mathcal{B}$ = matrix of coefficients obtained from the estimation

In multivariate multiple regression, each response variable is determined by its own regression model presented as:

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_{w} \end{pmatrix} = \begin{pmatrix} \mathcal{B}_{01} + \ \mathcal{B}_{11}\, X_1 + \ \mathcal{B}_{21}\, X_2 + \cdots + \ \mathcal{B}_{v1}\, X_{v} \\ \mathcal{B}_{02} + \ \mathcal{B}_{12}\, X_1 + \ \mathcal{B}_{22}\, X_2 + \cdots + \ \mathcal{B}_{v2}\, X_{v} \\ \vdots \\ \mathcal{B}_{0w} + \ \mathcal{B}_{1w}\, X_1 + \ \mathcal{B}_{2w}\, X_2 + \cdots + \ \mathcal{B}_{w2}\, X_{w} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_{w} \end{pmatrix} \qquad 4.6.2$$

Where the dependent variable is $Y_j^T = (Y_{i0}, Y_{i1}, \dots ; Y_{iw})$, predictor variable values $X_i = (X_{i0}, X_{i1}, \dots ; X_{jv})$ and regression coefficients $\mathcal{B}_i = (\mathcal{B}_{i0}, \mathcal{B}_{i1}, \dots ; \mathcal{B}_{iv})$.

Given that $E(\varepsilon) = E\left(\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_{w} \end{bmatrix}\right) = 0, Var\ (\varepsilon) = \Sigma$, the multivariate normal distribution for Y_{iw} is $Y_{iw} \sim N_{w}(\,X_i \mathcal{B}, \Sigma)$.

Thus, the normal multivariate density function (when the Σ is positive definite) is

$$f\left(Y_j \middle| \mathcal{B}, \Sigma\right) = (2\pi)^{\frac{w}{2}} |\Sigma|^{-\frac{1}{2}} exp\left(-\frac{1}{2}\left(Y_j - \mathcal{B}X_j\right)^T \Sigma^{-1}\left(Y_j - \mathcal{B}X_j\right)\right) \qquad 4.6.3$$

The matrix $\mathcal{B}$ of least-squares estimates of the regression coefficients is obtained from

$$\hat{\mathcal{B}} = (X^T X)^{-1}(X^T Y) \qquad 4.6.4$$

Specifically, the model estimated to examine the effect of bipolar tendencies on risk attitude is presented as:

$$Y(CPT\ parameter\ values) = \mathcal{B}_0 + \mathcal{B}_1 bipolar + \mathcal{B}_2 mood + \mathcal{B}_3 bipolar * mood + \mathcal{B}_4 age + \mathcal{B}_5 gender$$

4.7 Summary

This chapter begins with a conceptual framework that show how this thesis is designed to build on previous studies but goes further to link issues separately examined in previous studies. Specifically it shows how the study is able to examine the risk/uncertainty attitudes of participants and the connection between decision-making behaviour. It also highlights the procedure and methodologies employed to link attitudes to risk and uncertainty with mental health related factors.

To achieve the objective of estimating farmers' attitudes to risk and uncertainty in different context and content domains, this thesis uses both non-parametric methods - relating to the patterns that characterise participant choices and their determinants; and parametric models – based upon cumulative prospect theory as it extends to continuous prospects. This chapter shows how the CEU model estimated in this study has direct correspondence with CPT specifically under additivity of the subjective probability measures. It describes the steps involved in estimating the individual parameters from a Bayesian procedure and rationale behind the methods used to make inferences about the parameters.

In addition, Chapter 4 explains the generalized estimating equations procedure used to estimate the determinants of prospect choice. The objective of examining the effect of bipolar tendencies on risk attitude are determined from estimating multivariate multiple regression while the relationship between risk attitude and decision to engage in off-farm income generating activities are determined from probit and multinomial probit models respectively.

Chapter 5

Experiment Design and Implementation

5.0 Introduction

This chapter covers details of the steps and processes of designing the experiment to the implementation of the field experiment. The data used in this study was obtained using two data gathering tools – experiment and questionnaire. First, data relevant to estimating choices and attitudes under conditions of risks and uncertainties was collected using an interval '*lottery-style*' lab-in-field experiment that is as realistic as discrete lotteries but more indicative of the kind of choices made by farmers on a day-to-day level. Second, a two-part questionnaire was given to participants to obtain information relevant to achieving the research objectives. The first section of the questionnaire captured socioeconomic characteristics while the second section covered bipolar disorder using a modified Bipolar Spectrum Diagnostic Scale (by Ghaemi *et al.,* 2005).

The sections that make up Chapter 5 are as follows. Section 5.1 details the concepts on which the experiment pivots, section 5.2 explains the experimental design, section 5.3 reports the implementation processes and section 5.4 documents the data collection steps.

5.1 Continuous or Discrete Prospects?

This section explains the rationale behind the design of the prospect choice experiment before proceeding to explain key concepts associated with the experiment.

The studies reviewed in Chapter 2 shows that the literature is replete with discrete *lottery* choice problems. However, continuous choices problems arguably better reflect everyday real world problems. Everyday examples include our daily commute time to work, the yield of a crop, the change in an asset price, the interest rate on a loan *etc.* The following examples put in context a typical discrete and continuous lotteries in the risk case:

While a discrete lottery is typically presented as
Lottery Choices: Would you prefer A or B?

A:	10% *chance of winning* \$2	B:	10% *chance of winning* \$3.85
	90% *chance of winning* \$1.6		90% *chance of winning* \$0.10

The continuous lottery on the other hand takes the form of

Lottery Choices: Would you prefer A or B?

A:	Equal likelihood of winning any amount between \$1.6 and \$2	B:	Equal likelihood of winning any amount between \$0.1 and \$3.85

The main distinction between the continuous and discrete lotteries is that the number of possible values that the distribution of the continuous lottery has is infinite. Thus, the 'probability' that the payoff will assume a particular value is zero. Despite the prevalence of continuous choices problems in everyday problems, risky and uncertain real-life decisions have typically not been modelled using continuous lotteries. Instead, researchers relied on lotteries that have discrete probabilities attached to outcomes. To bridge this gap, the experiment in this study is based on interval prospect-choice design which takes into consideration key factors that defines a good elicitation technique.

5.1.1 Reality viewpoint

While this study acknowledges that in economics it is impracticable to exhaustively represent reality with pinpoint accuracy in an experiment, however being certain that the findings will reflect real life decisions is only possible if the structure of the experiments corresponds to the what participants encounter in real life. To bring into context the above argument, below is a typical instance where farmers in Nigeria were presented with hybrid maize:

> *"…under good management and weather, IITA maize hybrids A0905-28 and A0905-3 are reported to have the capacity to produce 6-9 tons/ha (Seed Management Enterprise Institute (SEMI), 2012)".*

While farmers are also aware that the competition hybrid *Oba 98* have potential yield of 6.5 – 8 tons/ha. The farmer in reality may (or not) have equally likely chance of obtaining a yield between the minimum and maximum *ceteris paribus.* Presenting this information as a discrete lottery for instance *say* - an equal chance lottery with 50% chance of 6tons/ha and 50% chance of 9tons/ha will be misleading as it does not capture all other yield possibilities in-between.

One of the arguments often put forward by the proponents of simple discrete outcomes in explaining risk attitude is the complexity of the model needed to adequately handle experimental designs where lotteries take the form of continuous distributions over outcomes since most of the leading theories were originally developed to handle discrete outcomes. However, this currently does not pose a problem as extensions of most of the leading theories (including the CPT and CEU as discussed in Chapter 3) can sufficiently handle such cases. In the light of this assertion and particularly as the participants of this study (farmers) are constantly being faced with information where possible outcomes are styled as interval 'lotteries', the design of the experiment puts reality before analytical convenience.

5.1.2 Cognitive perspective

Popular elicitation methods have reported inconsistencies when various elicitation tools are applied to artefactual experiments in developing countries (see Charness & Viceisza 2015; Brick, Visser & Burns 2012). It has been argued by some studies (*e.g.* Jacobson & Petrie, 2009) that inconsistencies arise from cognition among several popular elicitation techniques. Even comparison between methods using the same participants has resulted in significantly different effects. For instance the EG method discusses in Chapter 2 has been reported (see Dave, Eckel, Johnson & Rojas, 2010) to outperform the HL task in terms of ease of comprehension and reliability. Albert & Duffy (2012) criticised the EG task based on its complexity and low intuitiveness in the way it is portrayed to participants. Similarly, Coot *et al*., (2013) have reported high percentage of misunderstanding in a modified HL task even when effort was made to modify the task to the level of participants. Csermely & Rabas (2015) corroborates this finding and reported that varying both the possible outcomes and probabilities imposes cognitive burden, which leads to inconsistencies.

In the works of Sutter *et al.,* (2015) and Dasgupta *et al.,* (2016) the importance of taking into consideration the cognitive load at the design phase such that the experiments are simple enough to comprehend while simultaneously presenting little or no difficulties to implement is emphasised. However, experiments (especially the MPL's) can only be successful if participants show good understanding of basic probability concepts. Researchers have made significant efforts to simplify the process using techniques such as coloured marbles in a bag (see Humphrey & Verschoor 2004; Harrison *et al.*, 2010) balls in an urn (Tanaka *et al.,* 2010; Abdellaoui, Klibanoff & Placido, 2015). However, the explanation of probabilities still proves difficult to communicate to participants with low level of education. The quest to simplify some of the aforementioned techniques has pushed the design even further away from reflecting day-to-day real problems.

Consequently, this thesis is built on evidence that changing probabilities while keeping the outcomes fixed is not the most suitable elicitation instrument to be used in developing countries given the complexity this design possess[34]. In addition, graphical compared to tabular presentation and numerical probabilities enhances cognition[35] and retains concentration. Therefore, the need for a tailored experiment that is realistic and suits the level of cognition of the participants was one of the drivers of this study. As discussed in section 5.2 this thesis strips the '*lottery*' design of changing probabilities and fixing outcomes (*e.g.* as in Holt & Laury, 2002). Similarly, this study avoids fixing (discrete) probabilities and changing outcomes (for example in Jacobson & Petrie, 2007). This study altogether circumvent such mathematical jargon[36] by replacing lotteries that have discrete probabilities with lotteries having continuous probability distribution.

In summary, the applied work in this thesis is motivated by the fact that continuous lotteries are at least as realistic as discrete lotteries and more indicative of the kind of choices made by farmers on a day-to-day level. Moreover, continuous lotteries appear not to be any more cognitively demanding than discrete lotteries. Indeed, they may be even simpler to comprehend.

[34] Brick, Visser & Burns (2012) is one of the literature that provides such evidence.
[35] Further evidence in favour of this arguments can be found in Bodemer & Gaissmaier, (2012); Visschers, Meertens, Passchier & de Vries, (2009), Armel, Beaumel & Rangel, (2008); Krajbich, Armel & Rangel, (2010) and Dambacher, Haffke, Groß & Hübner (2016).

[36] By using simple concept such as "equally likely" it was possible to avoid the cognitive load that accompanies communicating probabilities to participants.

5.1.3 The "*equally likely*" Concept

For a continuous prospect under risk, the density needs to be specified. The simplest way to do this is to specify a uniform distribution thereby making the term "equally likely" a key concept in this thesis. The term *equally likely* was communicated to participants as a case where all events of a sample space have the same likelihood of occurring. Notably the context in which this term was used in this thesis differ from the discrete case with finite outcomes *e.g.* "50/50" prospect in which a probability mass function is specified. Rather the focus here was on a uniform distribution in which infinite number of outcomes are equally likely to occur. For equally likely lotteries with uniform continuous outcomes, the chances of any one payoff value occurring is zero (*i.e.* for all values of $x, P(X = x) = 0$) since the possibilities of any real number within the interval *say* [a, b] is infinite.

Attitudes towards risk as opposed to uncertainty, were elicited by specifying that all outcomes over the specified interval were 'equally likely'. Uncertainty was communicated by indicating to farmers that one outcome within the specified interval would be realised but without the specification of an associated probability density. For example, Figure 3a in section 5.2 below is a uniform continuous distribution in which prospect A is *equally likely* to take any value in the range of [₦4,280 to 7,358]. While prospect B is *equally likely* to take any value in the range of [₦5,361 to ₦6,315] (thus specifying a uniform probability density). It was emphasised and demonstrated to participants' that in the case of risk, each prospect resulted in an infinite number of possible payoffs within the given range [*i.e.* ₦4280 to ₦7358 for prospect A and ₦5,361 to ₦6,315 for prospect B]. Thus, there was no reason to believe that the frequency of occurrence differ for any value within the given interval of values. As for the case of uncertainty, when the set of continuous prospects are presented, the information about probability density is withheld. Details of the techniques used to distinguished risk from uncertainty in the field in a manner that participants understood the tasks under both conditions is discussed in subsections 5.4.2 and 5.4.3.

5.2 The Design

The experiment used in this study was designed to examine the risk and uncertainty attitudes of participant by observing their preference over a series of prospect pairs. The seven (7) types of prospect pair are presented in Figure 2. Of each of the seven (7) types of prospect pairs, the top prospect (prospect A hereafter) was more 'risky' and had a greater variance than the bottom (prospect B hereafter).

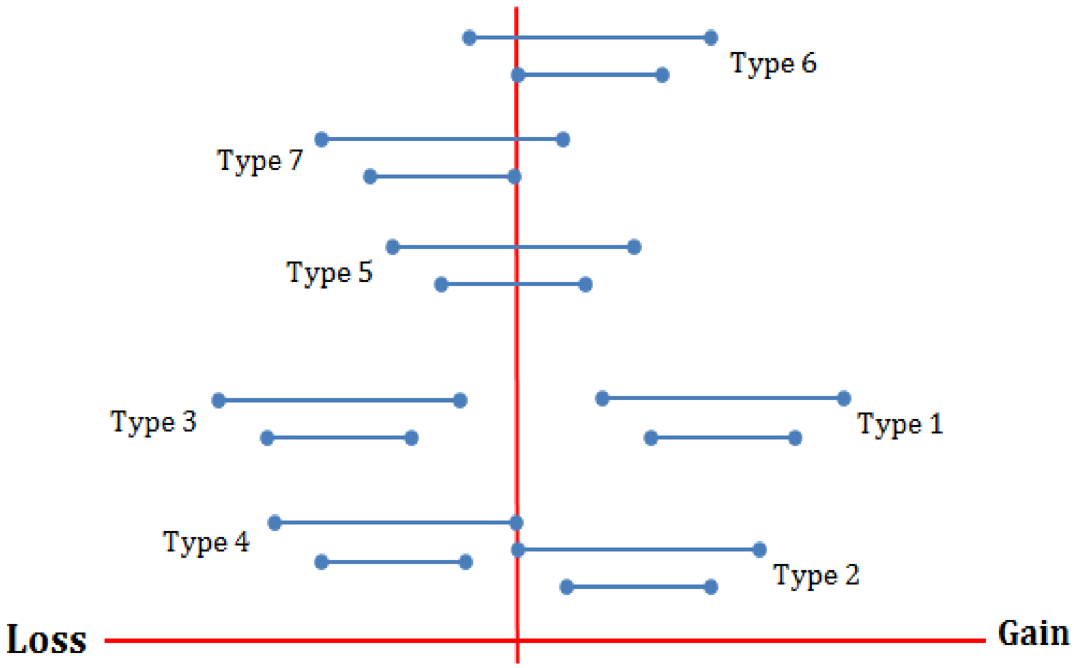


Figure 2. Types of prospect pairs

Type 1 is unconstrained in the gain domain. As an illustration under conditions of risk, the set of prospects presented in Figure 3*a* is *Type1* and shows that a DM is *equally likely* to earn any amount between ₦4280 and ₦7358 if he/she chooses Prospect A; while for Prospect B he/she is *equally likely* to earn any amount between ₦5361 and ₦6315. *Type 2* has the lower bound of the outer prospect at zero in gain domain. For example, the set of prospects presented in Figure 3*b* is *Type2* and shows that a DM is *equally likely* to earn any amount between ₦0 and ₦8662 if he/she chooses Prospect A; while for Prospect B he/she is *equally likely* to earn any amount between ₦3579 and ₦6108. Comparing *Type 1* to *Type 2* it becomes clear that while both are within the gain domain, the lower limit of prospect A in *Type 1* never drops to zero unlike *Type 2* where the lower limit of prospect A is always 'pegged' at zero.

Similarly, for the time context under risk; the set of prospects presented in Figure 3*c* is *Type3* and shows that a DM is *equally likely* to lose 54 minutes and 8 hours 36 minutes should the DM choose prospect A or *equally likely* to lose 4 hours 36 minutes and 5 hours 24 minutes if the DM picks prospect B. On the other hand, the set of prospects presented in Figure 3*d* is *Type4.* The difference between *Type 3* to *Type 4* is that while both are within the loss domain, the lower limit of prospect A in *Type 3* never drops to zero unlike *Type 4* where the lower limit of prospect A is always 'pegged' at zero. Details of the manner in which the entire experiment was presented to respondent is reported in Appendix 3.

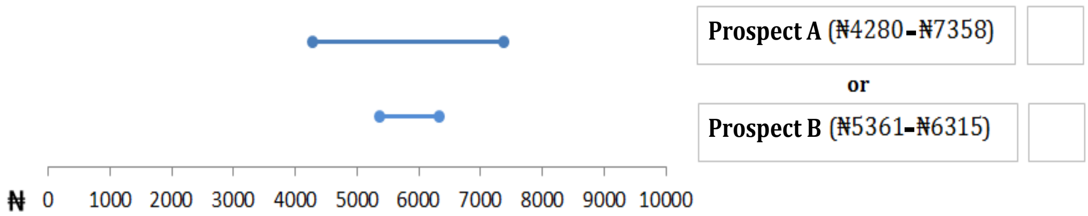


Figure 3a. Sample of *Type 1* prospect in monetary context (gain domain)

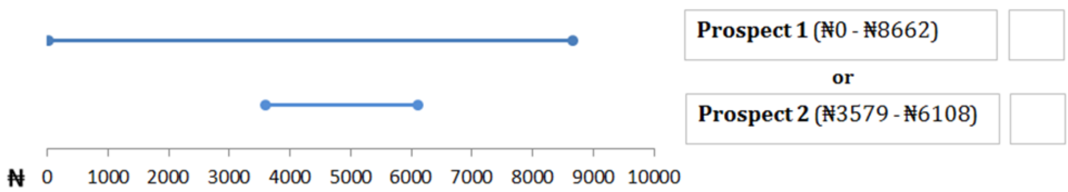


Figure 3b. Sample of *Type 2* prospect in monetary context (gain domain)

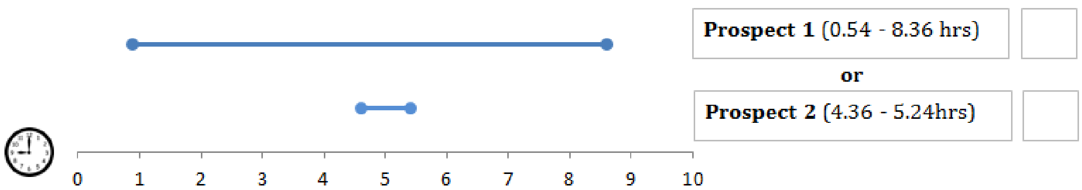


Figure 3c. Sample of *Type 3* prospect in time context (loss domain)

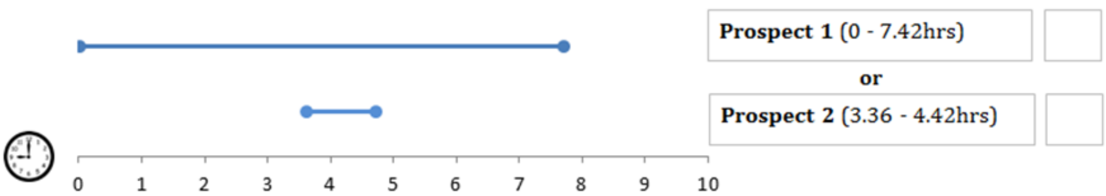


Figure 3d. Sample of *Type 4* prospect in time context (loss domain)

In summary, *Type 1* is unconstrained in the gain domain*.* *Type 2* has the lower bound of the outer prospect at zero in gain domain. *Type 3* is unconstrained in the loss domain. *Type 4* has its upper bound of the outer prospect at zero in the loss domain, *Type 5* - unconstrained in the mixed domain, *Type 6* has the inner prospect of the lower bound constrained to zero in the mixed domain, *Type 7* has its inner prospect upper bound constrained to zero in the mixed domain. The essence of the different types[37] was to cover as many domains of interest to this study and as wide a range as possible[38].

The prospects were computer generated random uniform lotteries on the 0 -100 interval. A large number of prospects pairs of each of the 7-*types* where generated in the first instance. The certainty equivalents of each of the prospect pairs were then calculated under expected utility for a ladder of "symmetric" power utilities across the gain and loss domains. These spanned from substantial risk seeking to strong risk aversion (2|2, 1.25|1.25, .99|.99, .5|5, .1|.1, .05|.05). Prospects pairs were kept only if there would be a switch from one of the prospects to another over this range of preferences. Thus, a prospect pair were retained when there was a difference in the certainty equivalents that would ensure there would be a difference in the choices made by participants' with different "risk profiles". Then, the prospect pairs where ranked according to those where switches would be made at different points in risk preference ladder (for all 7-*types*). Finally, a subset of the prospect pairs were chosen that had a range of switching points at different points in the ladder.

Each participant had to make a choice between Prospects A or B in which case Prospect A was by nature more 'risky' than B since prospect B is always contained in Prospect A and Prospect A always had a higher variance. This process continued along the choice tasks beginning with Prospect A having a smaller EV compared to Prospect B, as such a risk averse participant is expected to choose Prospect B over A. As the EV of Prospect A becomes larger than B in subsequent choice pairs, a risk

[37] *Note*. Type1 and Type2 are subtasks framed as a gain and jointly referred to hereafter as gain domain task. Similarly, Type3 and Type4 are subtasks framed as a loss and jointly referred to hereafter as loss domain task while Type5, Type6 and Type7 are subtasks which consist of both gains and losses and jointly referred to hereafter as mixed domain task.

[38] The entire experiment is presented in Appendix 3.

averse participant is expected to switch to Prospect A from B. Using both parametric and non-parametric approaches, the study estimates risk and uncertainty attitudes from the choice of the prospects of participants and the switching point of each participant.

Monotonic switching is not imposed in this study. One of the main reason for this was to ensure participants behaviour were observed when faced with real problems without imposing added assumptions on preferences. Further, it provides the platform to possibly examine any inconsistencies in choices. The proportion of participants that violated monotonic switching was minimal (accounting for only about 6%). This low percentage suggest that it was the innate behaviour of participants was captured rather than artefacts of the experiment.

The participants were expected to choose between a pair of prospects under each condition as shown in Figure 3. The conditions (risk and uncertainty) consisted of decision task covering monetary and non-monetary[39] context; across the gains, losses and mixed content domains as presented in Figure 4.

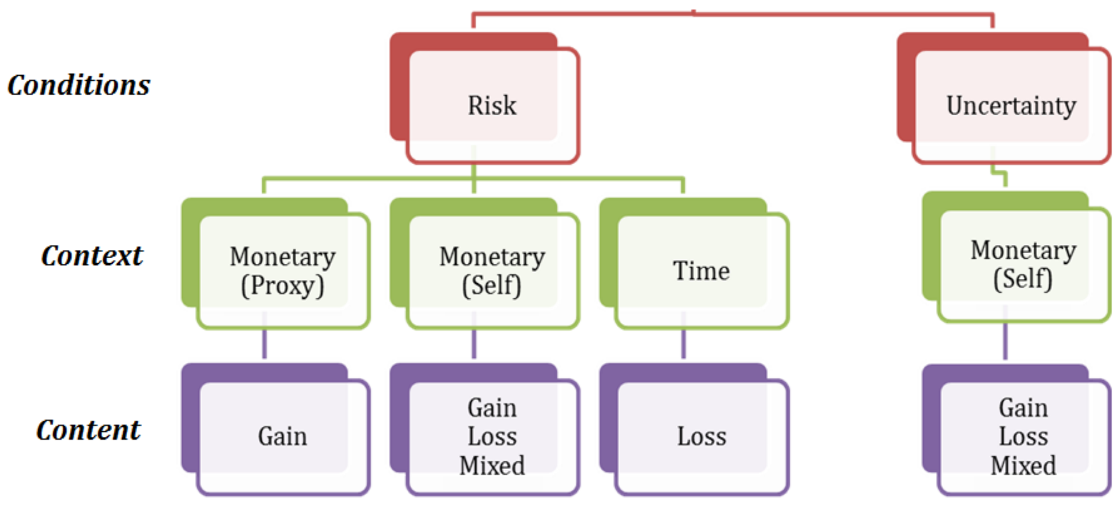


Figure 4. Conditions, Contexts and Contents domains

Each participant was presented with 90 pairs of prospect choice tasks spread across the different context and content domains under risk and uncertainty. Specifically,

[39] The non-monetary context was not tested under conditions of uncertainty as the resources needed by the researcher and mental effort on the respondents would have been enormous given the large number of choice task each respondent would have had to be presented with.

10 tasks was allocated to the gain content domain under proxy-monetary context, 10 task each to gain and loss content domains under self-monetary context and 15 tasks to the mixed content domains under self-monetary context. For the time context, 10 tasks was allocated to the loss content domain. Similar proportions to the self-monetary context under conditions of risk was allocated to the content domains under uncertainty. The pattern of experiment for risk and uncertainty was largely similar. However, the difference was the introduction the “equally likely” concept (as discussed in 5.1.3 and detailed in the questionnaire in appendix) for the risk experiment while in the case of uncertainty this information was not provided.

Finally, a questionnaire (details in Appendix 4) which covered socio-demographic characteristics and information on participation in off-farm income generating activities as well as bipolar disorder tendencies was also administered to participants to obtain other relevant data to meet the objectives of this study.

5.3 Implementation

This section documents the activities carried out prior to and during the field survey. Specifically it covers the preparation and procedure employed during the pilot survey and data collection.

5.3.1 Survey Location

The survey location was Edo and Delta State of Nigeria as shown in Figure 5a. The coordinates for Delta and Edo States are 5.5325° N, 5.8987° E and 6.5438° N, 5.8987° E respectively.

Figure 5a. Map Showing the Study Area

5.3.2 Selection of participants

The study relied on data obtained from 160 small farm households with the target respondent being the household heads since they are responsible for decision-making. Multistage sampling technique was used to obtain the respondents of the study. As shown in Figure 5b, the first and second stages depended on purposive[40] selection of the country Nigeria and then two states (Delta and Edo) within Nigeria.

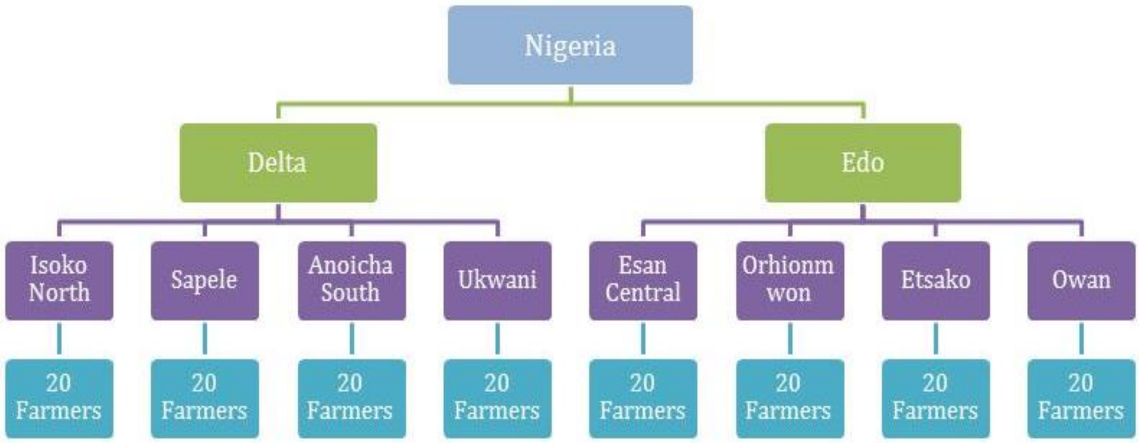


Figure 5b. Stages in Obtaining Respondents

Stage 3 involved the random selection of 4 Local Government Areas (LGA's) form each of the States (bringing the total LGA's to 8) while in stage 4, twenty (20) farmers each form the 8 LGA's were randomly picked to obtain the final sample size of 160 respondents.

5.3.3 Training of enumerators

Enumerators that assisted in carrying out the survey were trained by the researcher to ensure that they were familiar with the research and survey objectives as well as understood the questionnaire. They were also trained on how to make use of all supporting materials and administer the survey accurately and consistently without introducing any form of bias or noise. Overall, the researcher was fully responsible for coordinating the survey team.

---

[40] Delta State is purposively selected because part of the funding for the PhD research is provided by the Delta State University, Nigeria whose primary research interest lies within Delta State, while Edo State is chosen because it is broadly classified as having similar farming systems and agro-climatic conditions to Delta State but have its distinct cultural background. Hsee & Weber, (1999) find that culture has a significant impact on risk attitude.

5.3.4 Pilot

At the early stages of designing the experiment, a pre-pilot was conducted using volunteers from different background *i.e.* 4 farmers, 9 PhD students and 6 pensioners. The main reason for this was to obtain feedback from respondents of different education level on the simplicity and clarity of the experiment. The feedback obtained was used to further enhance the efficiency and effectiveness of the data collection instrument.

A pilot survey was conducted (using the target group *i.e.* smallholder farmers in Nigeria in this case) to determine how well the questions were understood and whether the content of each question was consistently given the same meaning by each respondent. This made it possible to identify ambiguous areas in the experiment. In addition, the pilot survey made it possible to estimate the resources and time required for each respondent to complete the experiment and questionnaire.

To achieve the objectives of conducting the pilot, the survey was completed by 30 farmers randomly selected from two communities via a recruitment process facilitated through extension agents and community leaders. The average time taken to complete the questionnaire was 1hour and 4 mins. The results for the pilot[41] is presented in Appendix 10. The main findings from the pilot were that participants' choices differ across content (*i.e*. gain, loss, mixed) domains. Specifically, under conditions of risk or uncertainty; majority of participants find the inner prospect more attractive for gains (and mixed task) and the outer prospect more attractive for losses. The proportion of participants that violated monotonic switching was minimal accounting for only about 11%[42].

The main feedback received was regarding the initial challenges in transiting from risk to uncertainty choice tasks. That is, some participants found it difficult to 'erase' from their memory equal likelihood when the instruction for subsequent choice task did not provide information regarding the specification of an associated

[41] Participants that took part in the pilot study were excluded from the main study and no data from the pilot study was included in the main results.
[42] This proportion reduced to 6% after incorporating feedback from the pilot.

probability density. In other to address this issue and assist with smooth transitioning between concepts; the demonstration using a wheel spinner (as discussed in section 5.4.2) was introduced to reflect the relevant concepts until respondents showed full understanding. Although this approach was time consuming as it increased the average completion time to 1hour 22mins, however it proved to be efficient and reliable as respondents' choices were their reflected uninfluenced independent decisions.

In addition, in response to the feedback from the participants, each of task was presented in the response sheets showing upper and lower bounds (an improvement to the initial blank answer sheet provided in the pilot) on which participants ticked their chosen options.

The observation on the field that continuous prospects are less cognitively demanding than discrete prospects and more related to decision problems farmers face on a day-to-day basis, the success in recruiting participants and in executing the experiment in line with the research plan jointly indicated that the main experiment was feasible subject to the aforementioned modifications.

5.4 Data collection procedure

Two sessions of data collection (morning and afternoon) ran per day with each session consisting of five participants. At the end of data collection, a total 158 respondents fully participated in the survey. The procedure adopted during the field survey consisted of four main sections namely; arrival and documentation check, introduction and briefing, choice task and decision experiment and submission.

5.4.1 Arrival and documentation check

Each meeting with respondents took place in a familiar location in each community were participants were drawn from. The field team that consisted of the PhD researcher and four (4) enumerators (who were trained by the researcher to assist in data collection) were responsible for welcoming participants. Each participant was required to present evidence of invitation (household ID number) provided by the local extension agent.

5.4.2 Introduction and briefing

The research aims and terms of participation were communicated to the participants in English and local languages after which the participants were asked if they understood and that they consented to these terms. At the beginning of the experiments a detailed explanation of the necessary concepts (described in section 5.1.3) relating to the choice task were explained using an unbiased wheel spinner. For the case of risk, a uniform probability density was specified by informing participants that all outcomes over the specified interval were 'equally likely'. Then the example in Figure 3*b* (which specifies that a DM is *equally likely* to earn any amount between ₦0 and ₦8662 if he/she chooses Prospect A) was repeatedly spun on the spinner. This demonstration continued for about 10 rounds until participants were sufficiently convinced from the outcome of the spins that every payoff point between ₦0 and ₦8662 was equally likely to occur and remains so if the spinner is spun repeatedly. For uncertainty, a similar demonstration to that of the conditions under risk was made however the key difference was that while the proportions on the spinner remain fixed for all 10 rounds under the risk demonstration, the proportions was repeatedly changed before each spin under uncertainty.

Specifically, participants' were told that they could earn any amount between ₦0 and ₦8662 if he/she chooses Prospect A but the associated probability density was not specified. Thus, each time before the dial is rotated the proportions 'allocated' to the payoffs between ₦0 and ₦8662 was varied. Such that in some cases it was possible for payoffs around the middle or within the boundaries (₦0 and ₦8662) to have greater likelihood of occurring (signifying '*not equally likely*') as well as some rounds in which all payoffs within the interval had equal likelihood of occurrence. Through this demonstration, participants grasped the concept that under uncertainty there was no specific information about the probability density as it could take any form ranging from uniform (*equally likely*) to non-uniform (*not equally likely*) should the spinner be spun repeatedly. This step was necessary to prevent noise that otherwise arose from cognitive barrier in the pilot.

Further, it was emphasised that there was no right or wrong answer. Thus, it was expected that participants provided genuine answers regarding their choice among the task. Participants were also informed that one of their prospect choices would determine payment for participation at the end of the experiment for those who completed the interview. Thereafter, participants were requested to work independently.

5.4.3 Choice task and decision experiment

For the experimental sessions, the farmers were randomly placed in groups. Each group consisted of five (5) farmers who performed the tasks independently. Participants were presented with coded cards which determined the order[43] in which each set of experiment was presented. The set of experiments consisted of series of lottery-styled choice list from which participants were required to make choices between prospects. Each task was presented to respondents one after the other in the form of choice cards. This process ensured that respondents made their

[43] The 6 orders of experiment designed were ABCD, ABDC, ACBD, ACDB, ADBC and ADCB where A = *Risk in monetary domain (gain, loss, mixed)* B = *Uncertainty in monetary domain (gain, loss, mixed)* C = *Risk in time domain (loss only)* D = *Risk in proxy monetary domain (gain only).* There was no order effect in results reported in Chapters 6 and 7 tested using multivariate regression to examine the effect of order on risk and uncertainty attitudes.

choice on a particular prospect before proceeding to the next. Four trial questions preceded the actual experiment to test respondents' understanding and if respondents asked questions and raised concerns this were addressed by the enumerator.

With the onset of a new set of choice tasks such as from gains to losses respondents attention were drawn by the researcher and necessary explanations made (*e.g.* reminding participants that they have finished a gain domain task and are now moving to a task framed as losses). Further, moving from risk to uncertainty participants were also reminded of the outcome of the demonstration using the wheel spinner in order to ensure that no issues arising from comprehension of the concepts were created when participant progressed from one condition, content or context domain to another. This was also necessary to forestall the earlier challenges reported in the feedback from the pilot regarding transitioning between concepts as discussed in 5.3.4. However, care was taken to avoid causing a gain *vs.* loss or risk *vs.* uncertainty effect by making sure the reminder was subtle and emphasising that there was no wrong or right answer so participants are free to report their genuine preferences.

Furthermore, a two-part questionnaire was given to participants to obtain information relevant to achieving other research objectives. The first section of the questionnaire captured socioeconomic characteristics while the second section covered bipolar disorder using a modified Bipolar Spectrum Diagnostic Scale (by Ghaemi *et al.,* 2005).

5.4.4 Submission and payment procedure

For the sake of establishing incentive compatibility, participants were told beforehand that after the experiment they would be paid according to the choices they had made earlier in the experiment for one prospect chosen at random[44]. Due to practical and ethical issues one of each participants' choice from the gains only domain was selected and played using a uniform random number generator in

[44] Similar to the findings from other studies, Azrieli, Chambers & Healy (2018) test for incentive compatibility in lottery based experiment and reports that selecting and paying for one randomly-chosen problem stands out as more often than not as a credible incentive compatible mechanism.

which the integer had a value between (and inclusive of) the upper and lower bounds of the prospect selected. As for uncertainty, payment was determined from the gains only domain using a using a Gaussian random number generator. On average, the payment to each participant based on the prospect selected was ₦3245 (£7.20). In addition, participants were also given monetary payment by the researcher. The payment they received was equivalent to an average two days wage as compensation for time spent during the experiment. Notably, participants were not told beforehand that they would be compensated for their time to ensure that only those genuinely interested in participating in the experiment took part and to avoid any effect the payment will have on their decision. The total amount spent on the monetary for compensation of all 160 respondents for their time was ₦464,000 (£1031).

Participants were also provided with contact details of the researcher should they wish to be informed about the findings from the research. Two respondents withdrew during the survey without providing the reason for withdrawal since respondents were under no obligation to do so. However, no respondent indicated interest to withdraw post-field survey. Overall, the field survey response was successful as about 98% response rate was achieved.

5.5 Summary

In summary, Chapter 5 sets the context for the choice of continuous over discrete prospects, discussed the steps in designing the experiment and its implementation in the field. This study relied on cross-sectional primary data collected from farmers' using a combination of lab-in-the-field experiment and questionnaire. The experiments depended on continuous prospects, which is less cognitively demanding than discrete prospects and more related to decision problems farmers face on a day-to-day basis. Attitudes towards risk as opposed to uncertainty, were elicited by specifying that all outcomes over the specified interval were 'equally likely'. Thus, specifying a uniform probability density. Uncertainty was communicated by indicating to farmers that one outcome within the specified interval would be realised but without the specification of an associated probability density. With the aid of the experiment (split into *Type*s 1-7 prospects that spread across the gain domain, loss domain and mixed domains); data relevant to achieving objectives I-III *i.e.* evaluating risk and uncertainty attitudes was obtained. Also, questionnaires that covered both socio-demographic characteristics and bipolar disorder tendencies was used to obtain relevant data relevant to achieving objectives IV-V.

Section 2 – Empirical Results, Discussions and Implications

Chapter 6

Data Description

6.0 Introduction

This chapter describes the data obtained from farmers that participated in the experiment. It consists of demographic and socioeconomic characteristics of the sample as well as a detailed description of the farmers' preferences with respect to choice task experiment.

Chapter 6 uses graphs, proportions and non-parametric tests to describe and explain the choices made by participants during the experiment. In line with the Mean-Standard deviation theory discussed in Chapter 3 participants' choices under risk and uncertainty attitudes is estimated using GEE and Probit regressions.

The results reported here covers participants' choices patterns in different content (gain, loss & mixed) domains under conditions of risk and uncertainty. It also includes participants' choices in monetary & time context under risk. It concludes with results showing the effect of attributes of the interval prospect experiment on participants' choices.

Chapter 6 comprises three main sections. Section 6.1 is made up of summary statistics of demographic and socioeconomic variables, section 6.2 describes the choices over gains, losses and mixed prospects under risk and uncertainty while section 6.3 comprises results and discussions of mean-standard deviation estimation.

6.1 Demographic and Socioeconomic Characteristics

The data analysed in this section was obtained from the questionnaire accompanying the experiment as discussed in Chapter 5. As reported in section 5.4, 160 framers participated in the experiment of which 2 farmers withdrew before collation of the results. Therefore, the summary statistics presented in Figures 6-9 and Table 12 is obtained from the sample of 158 farmers. As shown in Figure 6, the age range of subjects is between 27 to 87 years with the largest population of age group falling into the 51-60 years category. The average age of 56 years suggests that farmers in this region are middle aged. As presented in Figure 7, there were more males (70%) than females (30%) in the sample. This dominance of males could be attributed to selection of participants based on household head who are the main decision makers.

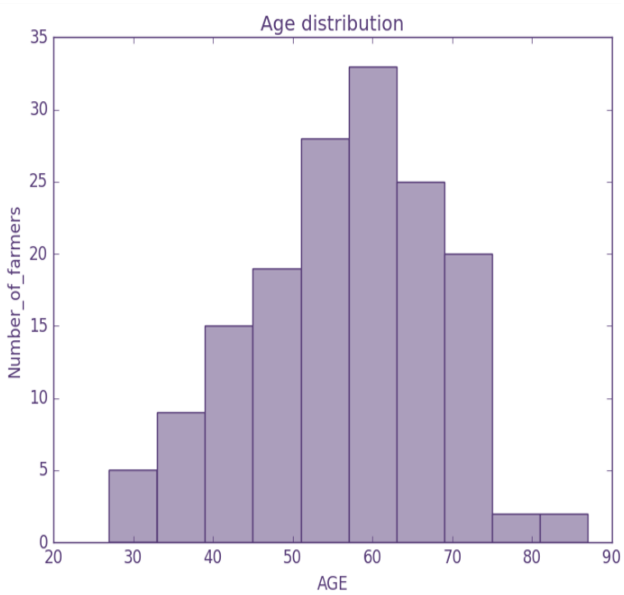


Figure 6. Age distribution.

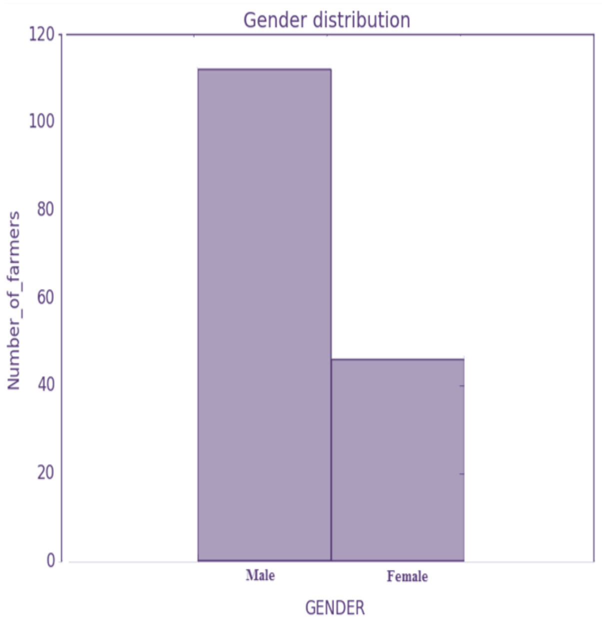


Figure 7. Gender distribution.

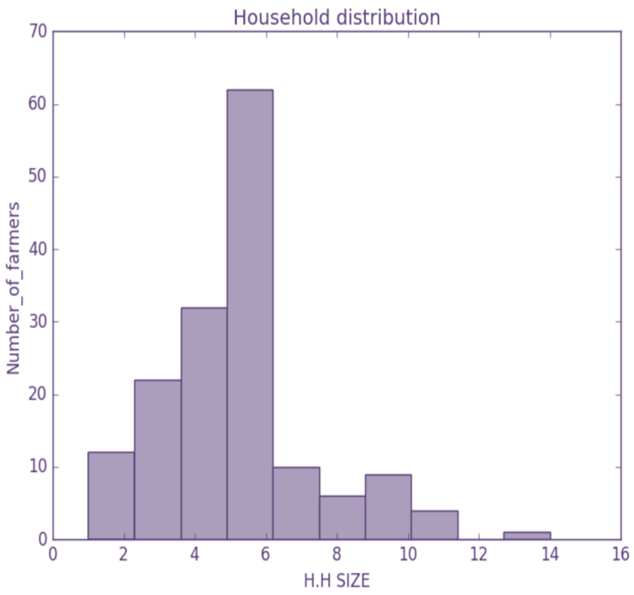


Figure 8. Household size distribution.

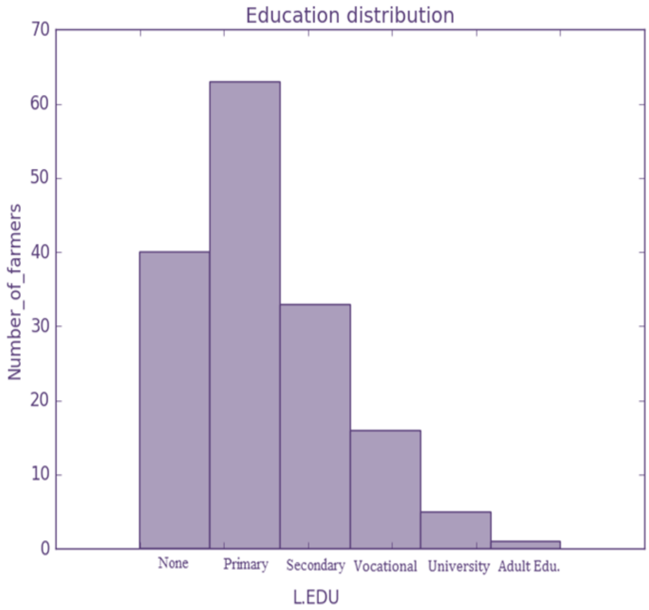


Figure 9. Education distribution.

As shown in Figure 8, farmers have an average household size of five (5) members. Figure 9 is a plot of the distribution of educational level attained. It shows that the level of formal education attained is low with about 65% completing primary education at the most. As presented in Table 12, the predominant primary occupation is farming accounting for about (95%). The average farm size was approximately one (1) hectare. About 88% of farmers' own their farms thus were directly responsible for making important economic decisions for the farm business. As shown in Table 12, the predominant categories of secondary occupation are employee, self-employed and worker. On average, the number of years in which farmers have engaged in farming is about 18 years while the average number of years that farmers have had secondary occupations was 10 years. This relatively long duration in occupation is a reflection of the fact that the sample consisted of farmers that have several years of experience at the helms of decision-making.

Table 12

Farmers' Economic Characteristics

Characteristics	Frequency		Distribution (%)	
Primary Occupation Type				
Farmer	150		95.0	
Others	8		5.0	
Ownership of Primary Occupation				
Own business	139		88.0	
Family (wage)	1		0.6	
Family (unpaid)	8		5.1	
Private Enterprise	7		4.4	
Government owned	2		1.3	
Others	1		0.6	
Secondary Occupation				
Yes	116		78.5	
No	42		21.5	
Secondary Occupation Type				
Employee	36		31.0	
Worker	43		37.1	
Self employed	37		31.9	
	Mean	**SD**	**Min**	**Max**
Years in Primary Occupation	18.49	12.40	2.0	54
Years in Secondary Occupation	10.18	8.74	1.0	54
Farm Size (ha)	1.08	0.59	0.2	4.0

In comparison to the most comprehensive agricultural data currently available in Nigeria *i.e.* Living Standard Measurement Survey (LSMS) - Integrated Surveys on Agriculture in Nigeria[45]; the sample characteristics in this study is representative of the farming population characteristics reported in the 2015/2016 LSMS. For instance, the LSMS reports that mean age is 49 years while the findings of this study is an average age of 56 years. According to the LSMS, 71% of the farming household head are male. This is similar to the 70% found in the sample data for this study. The LSMS reports average household size is 4 persons which also is similar to the average household size (of 5) recorded in the sample in this study. Finally, the average farm size as reported by the LSMS is 1.25 ha per household while the average farm size for farmers interviewed in this study was approximately 1ha per household.

[45] The Nigerian National Bureau of Statistics and Federal Ministry of Agriculture and Rural Development carried out the survey in 2015/16 with support from the World Bank.

6.2 Description of choice over gains, losses and mixed prospects under risk and uncertainty

Prior to presenting results obtained from a model-based analysis, preliminary results which categorises farmers as 'risk or uncertainty liking' or 'risk or uncertainty avoiding' based on their preference in the experiments (without taking into account any functional form or model) is presented. As deduced from the review of literature in chapters 2 and 3, in terms of estimating a DM's risk and uncertainty attitudes no estimation method is without limitations. Thus, applying a non-model based analysis will provide preliminary indication of the risk and uncertainty attitude of farmers' without the restriction that arises from assuming a specific model. Therefore, this section uses graphs, proportions and non-parametric methods to describe and explain the choices made by participants during the experiment.

6.2.1 Statistics of choices under risk and uncertainty (pooled subtasks)

The results presented in this section describes participants' choices under risk and uncertainty when participants were presented with the experiment described in Chapter 5. Recall, the experiment was designed such that participants had to make a choice between Prospects A or B wherein Prospect A was by nature 'more risky (uncertain)' than B since prospect B is always contained in Prospect A.

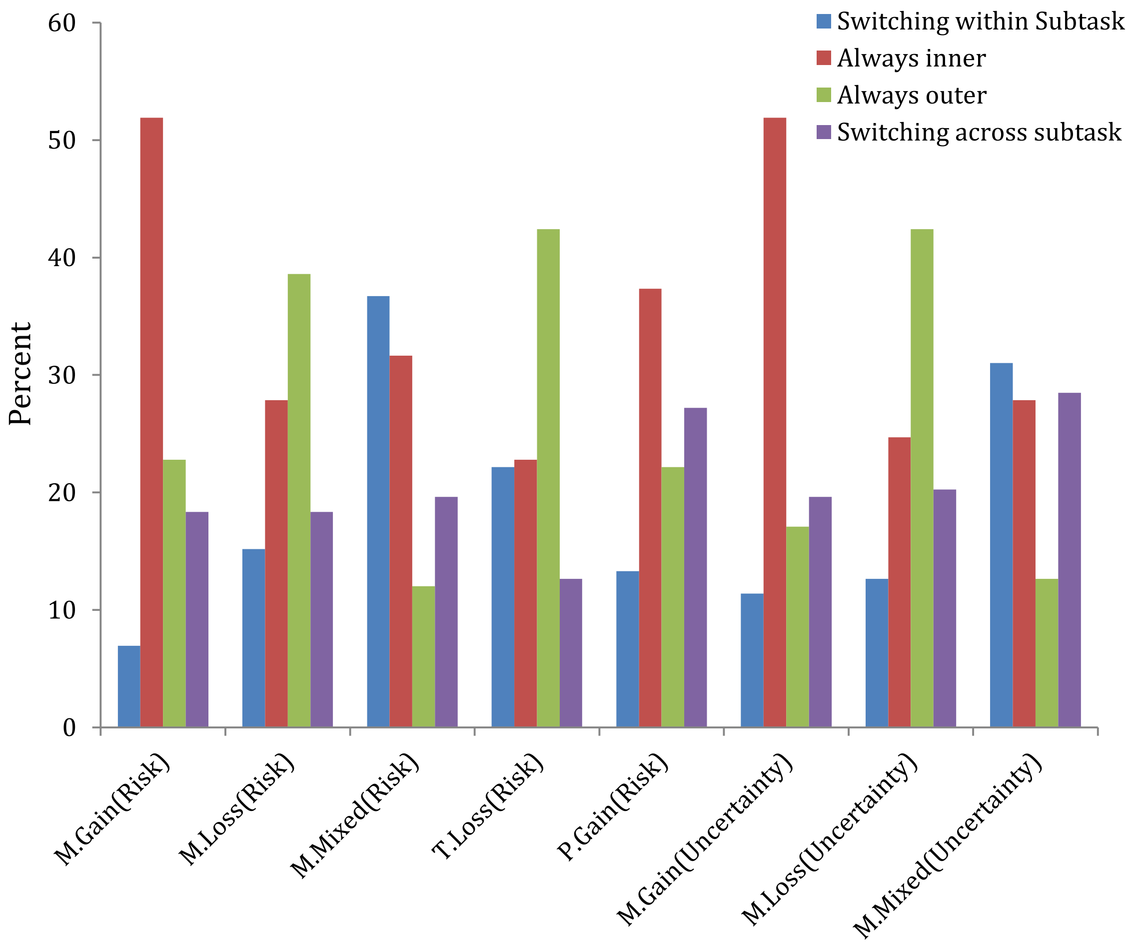
As discussed in Chapter 5, the nature of the prospects to which participants' choice was elicited is such that there was a difference in the certainty equivalents that would ensure there would be differences in the choices made by participants' with different "risk profiles". In addition, the prospect pairs where ranked according to those where switches would be made at different points in risk preference ladder *e.g.* as the EV of Prospect A becomes larger than B, a risk averse participant is more likely to switch to Prospect A from B.

A-priori it was expected that participants switch at some point (*i.e.* change their preference from Prospect A to Prospect B or *vice versa* as the experiment progressed) across all domains. However, not all the choices made by participants were in conformity with *a-priori* expectations. In addition, participants' choices differed across context and content domains as discussed in the sections that follows.

For the pooled subtask choices, all subtasks[46] within each specific domain are aggregated (pooled) into content (gain, loss, mixed) domain tasks. For example, the monetary task in the gain only domain consist of two subtasks. Recall in Chapter 5, Figure 2 showing the 7 types of prospect pairs; in the gain domain there are two types of prospect pairs *i.e. Types 1* and *2* which are each subtasks in the gain domain and jointly referred to as gain domain task in the pooled results. In the loss domain there are also two types of prospect pairs *i.e. Types 3* and 4. These loss domain subtasks (*Types 3* and 4) are jointly referred to as loss domain task; while in the mixed domain there are three types of prospect pairs *i.e. Types 5, 6* and 7 that consist of subtask spanning both gains and losses simultaneously and jointly referred to as mixed domain task in the pooled results presented in Figure 10.

A graphical presentation of the choices made by participants in conditions of risk and uncertainty is presented in Figure 10. *A priori* it was expected that participants will fall into two main groups consisting of 'switchers' within and across subtask. On the contrary, four patterns emerge from the results that portray participants' behaviour under risk and uncertainty suggesting heterogeneous attitudes toward risk as well as uncertainty. First those that switched their choice of prospect at some point within a subtask; for instance switched (*i.e.* from prospect A to B or *vice versa*) in a specific subtask (*e.g.* within *Type 1*). Second, participants that switched (*i.e.* from prospect A to B or *vice versa*) across subtask (*e.g.* choose prospect A throughout in *Type 1* and switched to prospect B at some point in *Type 2* or *vice versa*). Third, participants that consistently chose prospect B in each particular domain. Fourth, participants that always chose prospect A in each specific domain.

[46] Following the discussions in section 5.2 in Chapter 5, Figure 2 shows the 7 prospect pairs referred to as subtasks. *Types 1* and *2* are jointly pooled to make a gain domain task. *Types 3* and *4* pooled to make a loss domain task while *Types 5, 6* and *7* jointly make up what is referred to as a mixed domain task.



Note: M = Monetary prospect, T= Time Prospect, P=Proxy monetary prospect

Figure 10. Participants' patterns of behaviour under different conditions, context and content domains

6.2.1.1 Gain Domain

As presented in Figure 10, in gains domain tasks (referring to *Types 1 & 2*) participants' choices under risk and uncertainty fall into four patterns. This consist of individuals' that: (*a*) switched their choice of prospect at some point within a subtask, (*b*) participants that switched across subtask, (*c*) participants that consistently chose prospect B (inner prospect) in each particular domain and (*d*) participants that consistently chose prospect A (outer prospect) in the gain domain task.

Risk versus Uncertainty

Participants that switched within subtask for risk were approximately 6%. Out of the 94% that did not switch within subtask, over 51% of these did not switch from the 'safer' prospect B. This statistics suggests risk avoidance among majority of participants. The proportion is similar for participants' choices across subtask as about 18% only switched (*e.g.* in the first instance choose prospect A for *Type 1* tasks then switched to prospect B in *Type 2* or *vice versa*). As for the participants' choices under uncertainty as presented in Figure 10, those who switched within subtask were approximately 11%. Also, 19% switched across subtasks. Notably, 51% under uncertainty did not switch at all *i.e.* consistently choosing the inner prospect (prospect B) for all gain domain tasks. Thus, whether it is for risk or uncertainty; participants at the aggregate level find the inner prospect more attractive for gains. Since the inner prospect is by nature less "risky", this finding is an indication of participants' dislike for risk and uncertainty in the gain domain.

Hypothesis 4.1: Attitudes to risk differ from uncertainty (for gains)

McNemar's (1947) test that permits for evaluation of occurrence of statistically significant changes in proportions on a dichotomous variable between two groups of the same population was used to determine whether the proportion of the outer prospect as opposed to the inner prospect chosen by participants under conditions of risk is similar to conditions of uncertainty. The result presented in Table 12B show no statistical significant difference in the choices made in the gain domain under conditions of risk and uncertainty at the 1% level, (χ^2 = 1.74, p > 0.187). Therefore, we fail to reject the hypothesis that participants' choices under risk do not differ from uncertainty in the gain domains.

Do attitudes to risk differ when making decision on behalf of others (Proxy-gain vs. Self-gains)?

Comparing the choices made across the context domains of proxy-gain[47] *versus* self-gains only tasks; a smaller number of participants *i.e.* 37% (compared to 51% for

[47] For clarification wherein self-gain and proxy-gain are mentioned in the same sentence, 'self-gain' refers to risk for oneself in the monetary domain framed as pure gain only while proxy implies taking risk on behalf of 'other' person in the monetary domain also framed as pure gain only. In this thesis,

self-gain) continually picked the inner prospect suggesting significantly lower proportion[48] preferring the less 'risky' prospect when the decision was taken '*on behalf of another'* compared to *self*.

Hypothesis 5: There is significant difference in a DM's risk attitude when making personal vs. proxy decision.

McNemar's test was used to determine if there are differences in the overall choices farmers made in the *proxy-gain* and *self-gains* context domains. The result show statistical significant difference in the choices at the 1% level ($\chi^2 = 23.2$, $p < 0.001$). This statistical difference suggest context-specific risk attitudes *i.e.* risk attitude differ when faced with risk for oneself or risk on behalf of others. Hence, we reject the hypothesis that there is no significant difference in a DM's risk attitude under personal and proxy context. While further econometric tests are used to confirm the reason behind the significant difference in the choices farmers made in the *proxy-gain* and *self-gains* domain, however it may be as a result of responsibility effect and possibly the scales of the payoffs.

6.2.1.2 Loss Domain

The results presented here was obtained from participants' choices in subtasks framed as losses across both monetary and time contexts. Similar to the gain domain, participants are also categorised into four groups. This consist of individuals' that: (*a*) switched their choice of prospect at some point within a subtask, (*b*) participants that switched across subtask, (*c*) participants that consistently chose prospect B (inner prospect) in each particular domain and (*d*) participants that consistently chose prospect A (outer prospect) in the gain domain task.

Risk versus Uncertainty

In the loss domain task (*Types 3 & 4*), there was switching within subtask under risk by 15% of the farmers while 18% switched across subtasks. However, for uncertainty 12% switched within subtasks while 20% switched across tasks as

---

proxy is only tested in the gain domain. This study tested proxy only in the gain domain under conditions of risk.

[48] Chi-square test of the proportion confirms this ($\chi^2 = 6.26$, $p = 0.01$)

shown in Figure 10. The choice participants made in the loss-only domain is reversed compared to the preference in the gain domain tasks. Unlike the gain domain where the inner prospect was largely preferred, the predominant prospect choice in the loss domain was the outer prospect as observed by the majority (56% and 59% under risk and uncertainty respectively) picking the outer prospect overall. Notably, 38% in the case of risk and 42% under uncertainty did not switch at all (*i.e.* these group consistently chose only the outer prospect along all loss domain tasks) thereby portraying consistent risk/uncertainty seeking behaviour. This finding suggest that for both risk and uncertainty, participants at aggregate level behaves as though the outer prospect is more attractive for losses. Since the outer prospect is by design more "risky", these choice patterns are possible indicators of participants' risk and uncertainty seeking attitude in the loss domain.

Hypothesis 4.2: Attitudes to risk differ from attitudes to uncertainty (for losses)

To determine whether there was any significant difference in overall choices under conditions of risk and uncertainty in the loss domain, McNemar's paired test was performed. The result shows statistical significant difference in the choices made in the loss domain for risk compared to uncertainty as obtained from the test at the 5% level, (χ^2 = 6.11, p = 0.013). The mean values[49] indicate that under uncertainty (compared to risk), participants on average preferred the outer prospect (having larger variance) to the inner prospect. Thus, the hypothesis that attitudes to risk differ from uncertainty for losses cannot be rejected.

Do attitudes to risk differ with context domains (Time-loss vs Monetary-loss)?

A comparison of the choices made in the time-loss[50] context with the money-loss context domain task show some variation[51] in the number of participants that continually picked the outer prospect without switching (42% in the time context *vs.* 38% in the monetary context for losses). Similarly, there was difference in the proportion of participants that switched within subtask (15% in the monetary

[49] The proportion that chose the outer prospect for risk is 56% while for uncertainty 59%.
[50] Money-loss refers to risk for oneself in the monetary domain framed as pure loss only while time-loss implies risk framed as a loss to otherwise productive farm hours. In this thesis, time is only tested in the loss domain under risk.
[51] *Albeit* not statistically significant

context vs. 22% in the time context for loss) and across subtask (18% in the monetary context vs. 22% in the time context).

Hypothesis 3: There is difference in DM's risk attitude under time and monetary context

Non-parametric test was used to test for significance difference in the choices farmers made in the time-loss and money-loss context domains. The result show statistical significant difference in the choices as obtained from the McNemar's test at the 1% level ($\chi^2 = 16.9$, $p < 0.001$). This significant statistical difference indicates that risk attitude differ across context. Thus, the hypothesis that attitudes to risk do not depend on context is rejected.

Do attitudes to risk and uncertainty differ with content domains?

Having examined and cross-compared attitudes to risk to that of uncertainty in the gain domain on one hand and in the loss domain on the other hand in the preceding subsection; here the comparison is a condition specific test of choices within content domains. That is comparing gain *vs.* loss under risk as presented in *Hypothesis 1* and gain *vs*. loss under uncertainty as proposed under *Hypothesis 2*.

Hypothesis 1: Attitudes to risk depends on content domains

Non-parametric test was used to test for significance difference in the choices farmers made in gain and loss content domains under risk. The result show statistical significant difference in the choices as obtained from the McNemar's test at the 1% level ($\chi^2 = 113.3$, $p < 0.001$). This significant statistical difference indicates that risk attitude differ across content domains. Thus, the hypothesis that attitudes to risk does not depend on content domains is rejected.

Hypothesis 2: Attitudes to uncertainty depends on content domains

Similarly, under uncertainty the result show statistical significant difference in the choices farmers made in gain and loss content domains under uncertainty as obtained from the McNemar's test at the 1% level ($\chi^2 = 198.9$ $p < 0.001$). This significant statistical difference suggest that risk attitude differ across content domains. Therefore, the hypothesis that attitudes to uncertainty does not depend on content is rejected.

6.2.1.3 Mixed Domain

The results presented here was obtained from participants' choices in subtasks framed as mixed *i.e.* having both gains and losses as possible outcomes. The proportion of choices in the mixed domain task (*Types 5, 6 & 7*) is presented in Figure 10.

Risk versus Uncertainty

The pattern indicates greater switching within and across subtasks in the mixed domain compared to either the gain and loss domains. 36% under risk (*resp*. 31% for uncertainty) switched within subtask while 19% and 28% under risk and uncertainty respectively across subtasks. The most preferred choice in the mixed domain tasks was the inner prospect as over 63% and 62% under risk and uncertainty respectively picked the inner prospect overall. This predominant preference for the inner prospect in the mixed domain tasks is similar to the choice pattern reported for gains only tasks, which suggest participants' dislikes risk and uncertainty in the mixed domain.

Hypothesis 4.3: Attitudes to risk differ from uncertainty (for mixed)

McNemar's test was used to test for significance in the choices made in the mixed domains under conditions of risk and uncertainty. The result show no statistical significant difference in the overall choices of participants in the mixed domain for risk and uncertainty at the 10% level (χ^2 = 2.06, p = 0.151) in which case we fail to reject the hypothesis that in the mixed domain, attitudes to risk differ from uncertainty.

6.2.2 Statistics of choice under risk and uncertainty (separate subtasks)

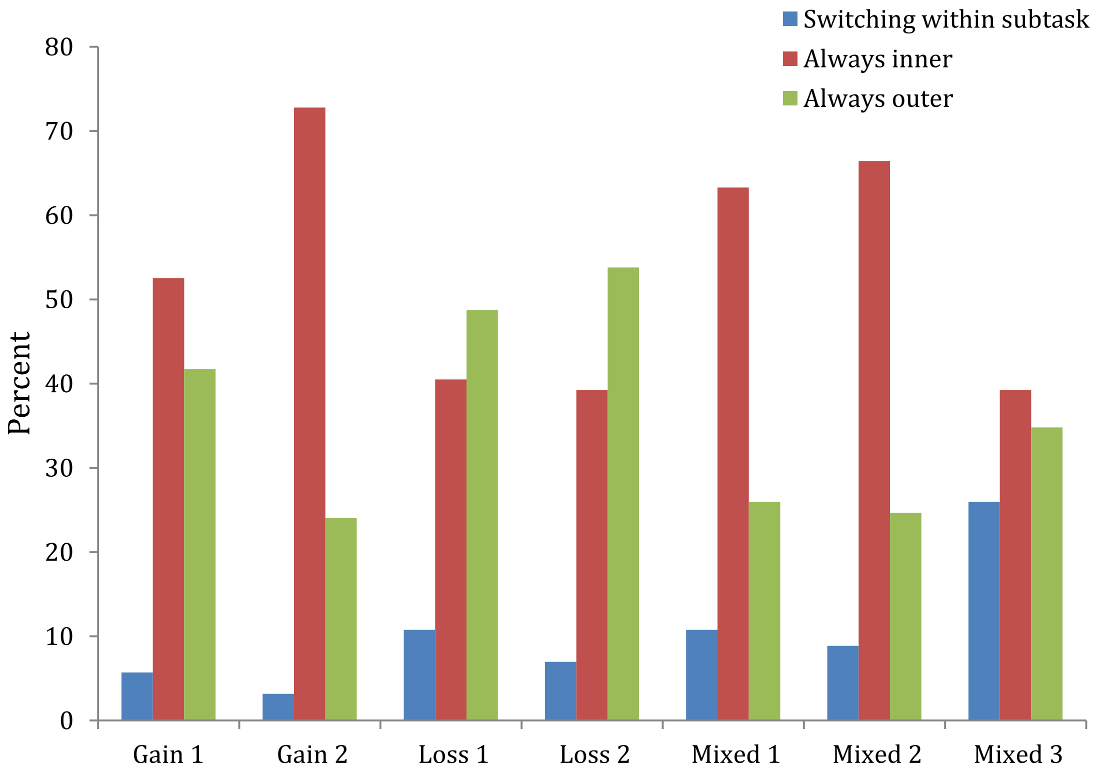
Figures 11 and 12 show the choice pattern further examined by sub-tasks under risk and uncertainty respectively but in the monetary context only[52]. The choices made under both conditions of risk and uncertainty have similarities as well as differences across the various content and context domains. The findings and discussion are presented. Recall that section 5.2 in Chapter 5 explains the 7 Types of prospect pairs; *Type 1* and *Type 2* being subtasks in gain domain task. *Type 3* and

[52] Comparison between subtasks in the time and proxy cases are presented in Appendix 6

Type 4 are subtasks in the loss domain task; while *Type 5, Type 6* and *Type 7* are subtasks which consist of a mixture of both gains and losses and jointly referred to as mixed domain tasks.

6.2.2.1 Gain Domain

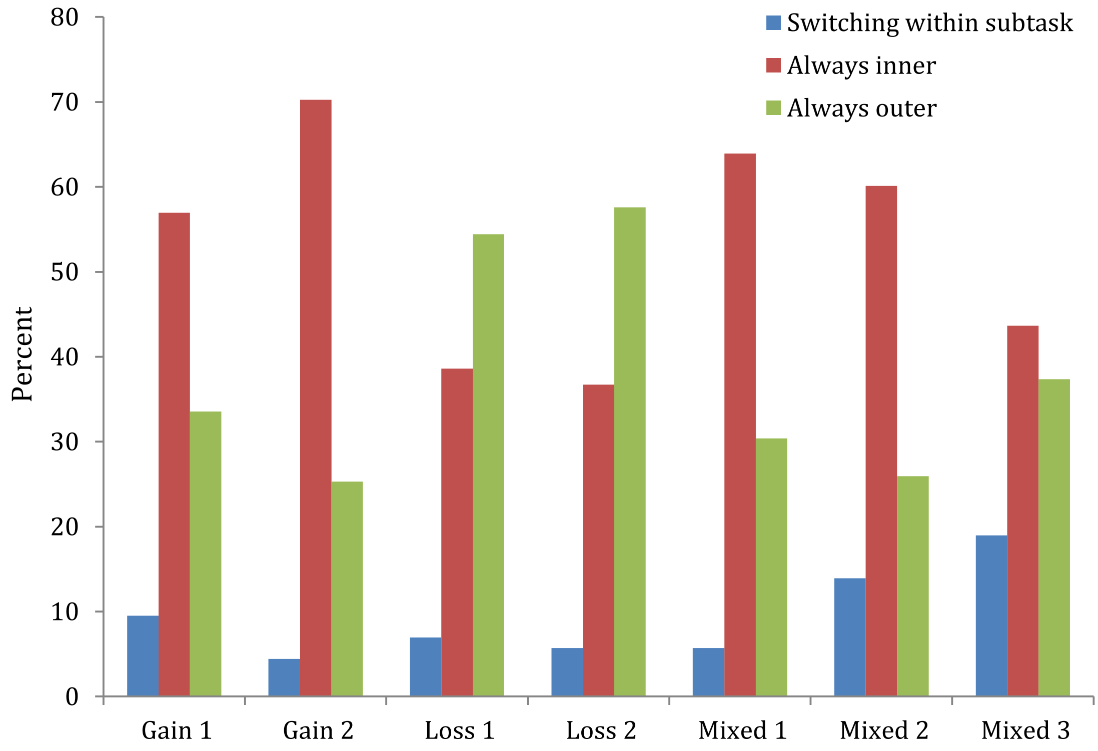
As shown in Figure 11**,** a significant proportion consisting of 52% and 72% in the subtasks (*Type1* and *Type2* respectively) never switched within a subtask as they always preferred the inner prospect under conditions of risk. Overall a larger proportion picked the inner prospect for Type2 (74%) compared to Type1 (56%).



Note. ***Gain1*** *= Type 1 - unconstrained in the gain domain,* ***Gain2*** *= Type 2* **-** *lower bound of the outer prospect at zero in gain domain,* ***Loss1*** *= Type 3* **-** *unconstrained in the loss domain,* ***Loss2*** *= Type 4 upper bound of the outer prospect at zero in the loss domain,* ***Mixed1*** *= Type 5 - unconstrained in the mixed domain,* ***Mixed2*** *= Type 6 - inner prospect of the lower bound constrained to zero in the mixed domain,* ***Mixed3*** *= Type 7 - inner prospect upper bound constrained to zero in the mixed domain.*

Figure 11. Patterns of behaviour by subtasks type under risk.

Similarly, under conditions of uncertainty, majority of participants (consisting of 56% and 70% for *Type1* and *Type2* respectively) chose the inner prospect consistently without switching under gains-only subtasks as presented in Figure 12. In aggregate, a larger proportion at some point in experiment picked the inner prospect for *Type2* (72%) compared to *Type1* (61%).



Note. ***Gain1*** *= Type 1 - unconstrained in the gain domain,* ***Gain2*** *= Type 2* **-** *lower bound of the outer prospect at zero in gain domain,* ***Loss1*** *= Type 3* **-** *unconstrained in the loss domain,* ***Loss2*** *= Type 4 upper bound of the outer prospect at zero in the loss domain,* ***Mixed1*** *= Type 5 - unconstrained in the mixed domain,* ***Mixed2*** *= Type 6 - inner prospect of the lower bound constrained to zero in the mixed domain,* ***Mixed3*** *= Type 7 - inner prospect upper bound constrained to zero in the mixed domain.*

Figure 12. Patterns of behaviour by subtasks type under uncertainty.

Hypothesis 1.1: Attitudes to <u>risk</u> differ within gain <u>content</u> domains

McNemar's test for differences in the overall choices farmers made in the *Type1* and *Type2* subtasks under risk show statistical significant difference in the choices at the 1% level, (χ^2 = 123, p < 0.001). The hypothesis that there is no significant difference in the choices of farmers within the gain domain under risk is rejected.

Hypothesis 1.2: Attitudes to <u>uncertainty</u> differ within gain <u>content</u> domains

Similarly, the McNemar's test result for differences in the aggregate choices farmers made in the *Type1* and *Type2* subtasks under uncertainty show statistical significant difference in the choices made at the 1% level (χ^2 =41.5 P < 0.001). Thus, the hypothesis that there is no significant difference in the choices of farmers in the gain domain under uncertainty is rejected. These findings suggest that the attitudes to risk and uncertainty depends also on the size of the prospects. While further analysis is needed to explain this significant difference between *Type1* and *Type2* (under both risk and uncertainty), this difference however could possibly be attributed to outer prospect of *Type2* being bound between zero and a positive payoff as against *Type1* in which both prospect payoffs are positive but non-zero bound.

6.2.2.2 Loss domain

As presented in Figures 11 and 12, the choices in the loss-only subtasks (*Types 3 & 4*) are reverse of the gains domain case. The predominant preference of participants under risk for losses was the outer prospect. The proportion that picked the outer prospect overall for *Type3* is 54% compared to 57% for *Type4*. Under uncertainty, a larger proportion (58%) picked the outer prospect for *Type3* compared to *Type4* (60%).

Hypothesis 1.3: Attitudes to <u>risk</u> differ within loss <u>content</u> domains

Non-parametric McNemar's test used to determine significance in the overall choices farmers made in the *Type3* and *Type4* subtasks under risk show statistical significant difference in the choices as obtained from the McNemar's test at the 5% level ($\chi^2 = 4.6$, $p = 0.032$). Thus we reject the hypothesis that attitudes to risk do not differ within loss content domains.

Hypothesis 1.4: Attitudes to <u>uncertainty</u> differ within loss <u>content</u> domains

In the same vein, under uncertainty the result show significant difference in the choices as obtained from the McNemar's test at the 10% level ($\chi^2 = 3.53$, $p = 0.060$). In which case, the hypothesis that there is no significant difference in the choices of farmers the loss domain under uncertainty is rejected.

Again the choice pattern across the different loss subtasks are subjected to further statistical estimations due to significant difference in the proportion of participants' choice in *Type3* and *Type4*. In line with the previous postulation, the difference observed could be attributed to outer prospect of *Type4* being bound between zero and a negative payoff as against *Type3* in which both prospect payoffs are negative non-zero bound. However, it goes to suggest that the attitudes to risk and uncertainty depends also on the size of the prospects even in the same content domain.

6.2.2.3 Mixed domain

Figure 11 and Figure 12 show that in the mixed subtasks (*Type5, Type6* and *Type7*) that the inner prospect was consistently chosen under risk and uncertainty respectively. Contrasting the choices in the subtask *Type5* (which is unconstrained in the mixed domain) against *Type6* (which had its inner prospect of the lower bound constrained to zero) yielded some interesting results.

Hypothesis 1.5: Attitudes to <u>risk</u> differ within mixed <u>content</u> domains

McNemar's test for significance in the overall choices farmers made in the *Type5* and *Type6* subtasks under risk show statistical significant difference in the choices at the 10% level ($\chi^2 = 3.5$, $p = 0.061$). In addition, a comparison of the choices in the subtask *Type5* (which is unconstrained in the mixed domain) *versus Type7* (which had its inner prospect upper bound constrained to zero) show statistical significant difference in the choices at the 1% level ($\chi^2 = 46.2$, $p < 0.001$). Thus, the hypothesis that there is no significant difference in the choices of farmers within the mixed domain under risk is rejected.

Hypothesis 1.5: Attitudes to <u>uncertainty</u> differ within mixed <u>content</u> domains

For uncertainty the results are different from risk as there is no significant difference in the choices at the 10% level, ($\chi^2 = 1.37$, p=0.241). On the other hand, a comparison of the choices in the subtask *Type5 versus Type7* show statistical significant difference in the choices at the 1% level (uncertainty: $\chi^2 = 81.2$, $p < 0.001$). Therefore, hypothesis that there is no significant difference in the choices of farmers within the mixed domain under uncertainty cannot be rejected.

This significant difference in the population choice between *Type5 and Type6* on one hand and *Type5* and *Type7* on the other hand may be connected with their design characteristics. For the *Type6* case, there is no chance of a getting a negative payoff compared to *Type5* while for the *Type7* case there is no chance of a getting a positive payoff compared to *Type5*. This may well result in farmers showing greater preference for the prospect that presents the possibility of attaining some 'desired levels'; in this case a possibility of making a gain. In addition, there may be the possibility that participants treat zero payoffs as either positive or negative relative to the value of other payoff in the same prospect. These possibilities are investigated in Chapters 7 and 8.

Table 12B
Summary of the Test of Hypotheses

Hypotheses	**χ^2**	**p-value**	**Significance**
Attitudes to risk differ from uncertainty (for gains)	1.74	$p > 0.187$	Not significant
Attitudes to risk differ from uncertainty (for losses)	6.11	$p = 0.013$	Significance at 5% level
Attitudes to risk differ from uncertainty (for mixed)	2.06,	$p = 0.151$	Not significant
There is difference in DM's risk attitude under personal and proxy context	23.2	$P < 0.001$	Significance at 1% level
Attitudes to risk depends on context domains	16.9	$P < 0.001$	Significance at 1% level
Attitudes to risk depends on content domains	198.9	$P < 0.001$	Significance at 1% level
Attitudes to risk differ within gain content domains	123	$P < 0.001$	Significance at 1% level
Attitudes to risk differ within loss content domains	4.6	$p = 0.032$	Significance at 5% level
Attitudes to risk differ within mixed content domains	3.50	$P = 0.061$	Significance at 10% level
Attitudes to uncertainty differ within gain content domains	41.5	$P < 0.001$	Significance at 1% level
Attitudes to uncertainty differ within loss content domains	3.53	$p = 0.060$	Significance at 10% level
Attitudes to uncertainty differ within mixed content domains	81.2	$P < 0.001$	Significance at 1% level

In summary, the results presented in section 6.2 suggest that participants' choices in the experiment are heterogeneous given the four patterns that portray participants' behaviour under risk and uncertainty. Also, whether faced with conditions of risk or uncertainty, participants find the inner prospect more attractive for gains (and mixed task) and the outer more attractive for losses. Since the inner prospect is by nature less 'risky', this finding is an indication of participants' dislike for risk and uncertainty in the gain (and mixed) domain; and liking for risk and uncertainty in the loss domain. The results also suggest that participants' choices differ across content (gain, loss, mixed) domains.

6.3 Results of Mean-Standard deviation Estimation

GEE regression follows an estimation of the model in equation 4.4.1iv in Chapter 4 and the results are presented in Table 13. In accordance with the literature discussed in Chapter 3, the Mean-Standard deviation (MSD) measures risk by its variance or standard deviation. In a scenario where a DM is faced with a risky and uncertain choice task; the 'rational' risk averse DM would *a-priori* prefer the option that has both the greater expected value and smaller SD. In the case where the expected values of the choice task are equal then the risk averse DM should prefer the alternative with the smallest SD.

Recall from section 4.4.1 in Chapter 4 that for the variables in Table 13 'Mean' and 'SD' refers to the differences in mean and standard deviation respectively between the payoffs of prospects A and B. 'Gain', 'loss' and 'mixed' indicates that the payoffs are strictly positive, strictly negative or mixed domains. 'ZB_outer_gain' implies that the gain domain task has the lower limit of the outer prospect bound at zero. 'ZB_outer_loss' means that the loss domain task has the upper limit of the outer prospect bound at zero. Similarly, 'lower_ZB_inner_mix' indicates a mixed domain tasks having the lower limit of inner prospect bound at zero while for 'upper_ZB_inner_mix' the mixed domain task has the upper limit of inner prospect bound at zero. In line with the predictions of the M-SD theory, an increase in the difference between the means of the outer and inner prospects will result in the rise in the likelihood of choosing the outer option.

As discussed in Chapter 4, the model from which the result in Table 13 is obtained includes content domain specific variables (*i.e.* gain, loss and mixed) in addition to zero constrained prospects. The dependent variable is binary which signifies the DM 'prefers the prospect with greater *variance* (prospect A) = 1'; 0 otherwise[53].

[53] The proportion of 1 and 0 in the data was approximately 1:2 so this was not an issue for estimation.

Table 13

GEE and Probit results showing marginal effect for determinants of lottery choice

	GEE (Probit)			Probit		
Variables	**I Pooled**	**II Risk**	**III Uncertainty**	**IV Pooled**	**V Risk**	**VI Uncertainty**
Mean	0.019***	0.024***	0.014***	0.019***	0.024***	0.014
	(0.006)	(0.007)	(0.009)	(0.004)	(0.004)	(0.005)
SD	-0.005	0.012**	-0.002	-0.005	-0.012	0.002
	(0.010)	(0.015)	(0.013)	(0.004)	(0.005)	(0.006)
Gain *x* SD	0.012	0.001	0.010	0.012	0.001	0.010
	(0.018)	(0.026)	(0.027)	(0.008)	(0.008)	(0.008)
Loss *x* SD	0.001	0.000	-0.003	0.001	0.000	-0.003
	(0.015)	(0.031)	(0.019)	(0.006)	(0.010)	(0.007)
Gain	-0.089***	-0.051	-0.114***	-0.089***	-0.052**	-0.114***
	(0.016)	(0.025)	(0.021)	(0.032)	(0.035)	(0.035)
Loss	0.058*	0.049	0.071*	0.057***	0.048*	0.071***
	(0.016)	(0.027)	(0.023)	(0.032)	(0.036)	(0.036)
Mix	-0.161***	-0.168***	-0.154***	-0.161***	-0.169***	-0.154***
	(0.020)	(0.029)	(0.028)	(0.031)	(0.034)	(0.037)
ZB[&]_Outer_Gain	-0.157***	-0.189***	-0.127***	-0.157***	-0.189***	-0.127***
	(0.017)	(0.024)	(0.027)	(0.028)	(0.032)	(0.038)
ZB_Outer_Loss	0.038	0.044	0.036	0.038**	0.044	0.036
	(0.017)	(0.029)	(0.024)	(0.029)	(0.036)	(0.037)
Lower_ZB_Inner_Mix	-0.043	-0.044	-0.040	-0.043**	-0.044*	-0.040
	(0.018)	(0.025)	(0.027)	(0.028)	(0.031)	(0.038)
Upper_ZB_Inner_Mix	0.183***	0.217***	0.150***	0.183***	0.217***	0.150***
	(0.018)	(0.026)	(0.026)	(0.034)	(0.039)	(0.042)

[&] ZB= zerobound *** p<0.01, ** p<0.05 and * p<0.1

Standard errors are in parentheses

No. of Observations = 11060 for pooled, 5530 for all others

Three variations of the GEE model are estimated; models I, II and III representing pooled (risk and uncertainty combined), risk only and uncertainty only respectively. In addition, three probit models (IV, V, VI) are estimated since its result is similar to the GEE under independence structure. Overall, the results indicate that the mean payoff of the prospect, the content domain (gain, loss or mixed) determine the likelihood of choosing the outer option *i.e.* prospect A. Note that a positive coefficient denotes the corresponding variable increases the likelihood of picking the outer prospect and *vice versa*.

Mean – As shown in Table 13, the coefficient of the '*mean'* effect is significant and positive for all estimated models. In line with the predictions of the MSD theory, the results show that for all six models, an increase in the difference between the means of the outer and inner prospects will result in the rise in the likelihood of choosing the outer option *i.e.* prospect A. However, this effect is relatively weak as evident from the small values of the estimated marginal effects.

Standard deviation (SD) – There was no significant effect of SD on the choice of prospects in all estimated Models except for Model II where there is negative significant relationship (β =-0.05, z = -2.28, p<.05) between standard deviation and prospect choice. This significant relationship denotes that as the SD increases, it decreases the likelihood of picking the outer prospect under risk condition. Again, this effect is relatively weak as the values of the estimated marginal effects are small however; this findings conforms to *a-priori* expectations.

Gain - The coefficient of '*gain'* is negative and significant in Models I (β = .038, z = -2.67, p<.01), III (β = 0.49, z = -3.12, p<.01) and IV (β =-0.23, z = -5.50, p<.01) suggesting that when a gain domain task is presented to the participants, there was increased likelihood of avoiding the outer prospect.

Loss – In contrast to the '*gain'* effect, '*loss'* has a significant but positive effect on prospect choice. This significant effect in Models I (β = .024, z = 1.91, p<.10), III (β = .30, z = 1.73, p<.10) and IV (β = .15, z = 3.52, p<.01) indicates that the likelihood of choosing the outer prospect increases when the task is in the loss domain. These findings are consistent with numerous findings in the literature predicting of risk avoidance for gains and risk seeking for losses.

Mixed - The mixed domain effect is negative and significant for models I, II, III and IV (β = -0.70, z = -4.74, p<.01), (β = -0.74, z = -4.55, p<.01), (β = -0.66, z = -3.85, p<.01), (β = -0.43, z = -8.05, p<.01) respectively; indicating greater likelihood of avoidance of the outer prospect in the mixed domain task. Notably, the increase in the probability of choosing the outer prospect is higher in the mixed domain than the gains only domain. Again, these results are in consonance with the findings in several risk/uncertainty decision-making literature.

Zero bounds prospects- The effect of *zero-bound-outer* prospect in the gain domain are negative and significant for models I, II III and IV (β = -0.69, z = -5.52, p<.01), (β = -0.83, z = -5.57, p<.01), (β = -0.56, z = -3.32, p<.01), (β = -0.42, z = -8.93, p<.01)[54] respectively. The relatively large estimated marginal effect in all four models supports previous findings in Section 6.2 that not only are participants more likely to avoid the outer prospect in the gains domain; but there is higher likelihood to specifically avoid the outer prospect when its lower bound is at zero. This result highlights the preference for substantive deterministic gains. In contrast, the coefficient of the *zero-bound-outer* in the loss domain (statistically significant in Model IV) highlights the findings in Section 6.2 that in the loss domain participants prefer the outer prospect *i.e.* prospect A; and are markedly more likely to choose the outer prospect when its upper bound is zero. Similarly, the effect of *lower-zero-bound-inner* in the mixed domain are negative and significant for models IV and positively significant for *upper-zero-bound-inner* in all six models thus further indicating that participants are likely to prefer the more risky/uncertain prospect if the alternative prospect has likelihood of a strictly negative loss occurring. This study refers to these attitudes hereafter as '*negligible gain avoidance'* (NGA) and '*negligible loss seeking*' (NLS). These unusual but insightful finding that it does matter to participants when one of the bound of the prospect was pegged at zero but the payoffs still remained strictly positive (or negative) was *a-priori* not expected.

[54] In addition, the significant negative (*resp*. positive) coefficient of lower-zerobound-inner (*resp*. upper-zerobound-inner) in the mixed domain for model IV implies that when the payoffs of the inner lotteries are confined to a negative (*resp*. positive) domain compared to the alternative lottery that is spread between gain and loss, the likelihood that participants prefer the outer lottery decreases (*resp.* increases).

One possible argument could be that '*NGA'* and '*NLS'* are nothing more than artefact of the design. This assertion is investigated and the findings presented in section 8.1 in Chapter 8. From a different perspective, it could be that participants adopted different decision rules that may well reflect those that are used in their day-to-day decision making even if it may not be "rational". Thus, the rest of Chapter 8 examined decision rules and alternative theories with the aim of providing further explanation on the phenomenon highlighted in this Chapter. The Chapter that follows is focused on further examining the risk and uncertainty attitudes of farmers using Bayesian procedure on CPT and the extent to which these aforementioned behaviours can be reconciled with CPT.

6.4 Summary

Recall that section 5.2 in Chapter 5 explains the 7 *Types* of prospect pairs; *Type 1* and *Type 2* being subtasks in gain domain task. *Type 3* and *Type 4* are subtasks in the loss domain task; while *Type 5*, *Type 6* and *Type 7* are subtasks which consist of a mixture of both gains and losses and jointly referred to as mixed domain task. The results obtained from graphs, proportions and non-parametric tests suggest that participants' fall into four choice patterns. First those that switched their choice of prospect at some point within a subtask; for instance switched (*i.e.* from prospect A to B or vice versa) in a specific subtask (*e.g.* within *Type 1*). Second, participants' that switched (*i.e.* from prospect A to B or vice versa) across subtask (*e.g.* choose prospect A throughout in *Type 1* but switched to prospect B at some point in *Type 2* or vice versa). Third, participants' that consistently chose prospect B in each particular content domain. Fourth, participants' that always chose prospect A or B in each specific content domain. Further, participants reacted differently to *Types 2, 6, 4* and *7* where the prospects' upper or lower bound were constrained at zero. Also, the findings suggest that participants' choices differ across context (personal, proxy & time) and content (gain, loss, mixed) domains.

Further, the results of GEE and probit estimation showed that the mean value of the prospects had effect on the choices participants' made and crucially, an increase in the difference between the means of the outer and inner prospects will result in the increase in the likelihood of choosing the outer prospects. The results also show that under risk and uncertainty; participants find the inner prospect more (less) attractive for gains (*resp*. losses). Since the inner prospect is by nature less "risky", this finding is an indication of participants' dislike (*resp*. love) for risk and uncertainty in the gain (loss) domain. Overall, there was higher likelihood of specifically avoiding the outer prospect when its lower bound is at zero – a phenomenon this thesis referred to as *negligible gain avoidance*. Similarly, in the loss domain participants' were more likely to choose the outer lottery when its upper bound was zero in what is referred to in this thesis as *negligible loss seeking*. In Chapter 7, the result in Chapter 6 is subjected to Hierarchical Bayesian CPT estimation to broaden the findings on participants' attitudes and further elucidate *negligible gain avoidance* and *negligible loss seeking*.

Chapter 7

Cumulative Prospect Theory (CPT) Results and Discussion

7.0 Introduction

The chapter presents and discusses results obtained from estimating the Hierarchical Bayesian CPT model discussed in Chapters 3 and 4. The results reported here will cover only (monetary) risk and uncertainty obtained from participants' responses to task *Types 1-7*. The results have been limited to these two cases primarily due to time and resource constraints of the author as well as the fact presenting results for every case would require a number of very long sections. Thus, the CPT analysis has been constrained to what the author considers the two most important cases (monetary risk and uncertainty). Therefore the analysis in this chapter is based on data obtained from 158 participants' over monetary pure gains, losses and mixed tasks along 35 decision rows resulting in a total of 5530 risk choices and 5530 uncertainty choices.

Although the estimates of the individual parameters were derived from a Bayesian procedure, inference about the parameters was *via* classical non-parametric test applied to the individual parameters extracted from the Bayesian mixed logit. *A proviso* the analysis below is therefore that this is a two-stage procedure and as with all two stage procedures there will be an associated bias to these tests. Notably, the standard CPT function is likely to struggle to deal with the behaviour highlighted in the section 6.3 in Chapter 6 *i.e.* phenomenon of *NGA* and *NLS* and significantly large number of non-switching at different points in risk preference ladder. This possibility leads to the bunching of individuals at the end of the parameter space implying appropriateness of using non-parametric tests.

Chapter 7 comprises of three main sections. Section 7.1 describes participants' risk attitudes over gains, losses and mixed prospects, section 7.2 describes participants' risk attitudes under uncertainty while section 7.3 compares the results in 7.1 and 7.2.

7.1 Attitudes to Monetary Risk

As discussed in Chapters 3 and 4, the utility and weighting functions fitted in this study are power utility (*see* equation 3.4.3) and Prelec II weighting function (*see* equation 3.4.9) functions respectively. The CPT estimation permitted different subjective value function for gains (α), losses (β) in addition to accommodating separate weighting function for gains (γ^+ and δ^+) and losses ($\gamma^-$and δ^-). This thesis impose restriction on the CPT parameters. The restriction are $\alpha \in [0.05, 2]$, $\beta \in [0.05, 2]$, $\lambda \in (0.05, 3)$, $\gamma^+ \in [0.25, 2]$, $\gamma^- \in [0.25, 2]$, $\delta^+ \in [0.25, 2]$, $\delta^- \in [0.25, 2]$, $\varphi \in [0, \infty]$ to enable the possibility of capturing different shapes of the value and probability weighting function.

The joint posterior parameter distributions which was estimated in python software[55] was obtained from Monte Carlo Markov Chain (MCMC) algorithm for 12,000,000 iterations out of which 2,000,000 iterations were discarded as burn-ins thus was not used to represent the posterior. In order to reduce correlation across retained posterior draws, 1 in every 1000 draws was extracted resulting in a total of 10,000 iterations. Visual observation of the trace plots confirms convergence of the MCMC draws.

To prevent misleading and unrepresentative values that might arise from reporting only the median as in Resende & Tecles, (2011), Abdellaoui *et al.* (2008) this study reports both the mean and median values. A description of the estimated parameters under risk is presented in Table 14. These results confirm the presence of heterogeneity among respondents (for instance 25%, 50% and 75% of the sample have β value of at most 0.12, 0.57 and 1.42 respectively). This corroborates the findings of Abdellaoui *et al.* (2008) and Resende & Tecles, (2011), that parameter estimates at individual level provides evidence of heterogeneity among participants.

The results in Table 14 further underline the non-normality of the distributions of individual preference parameters, also highlighting that using the underlying mean and variance parameters from the mixed logit as being indicative of the population

[55] I acknowledge and express my gratitude to my supervisor for writing the codes used for this estimation.

would be misleading. Therefore, for testing hypotheses, the individual preference parameters are used, in conjunction with non-parametric tests.

Table 14
Descriptive Statistic for CPT Risk Parameter under risk

Variables	Mean	Median	SD	Min	25%	50%	75%	Max
α	0.53	0.06	0.73	0.05	0.05	0.06	1.30	1.99
β	0.76	0.57	0.68	0.05	0.12	0.57	1.42	1.93
γ^{+}	0.73	0.34	0.59	0.26	0.27	0.35	1.33	1.96
γ^{-}	0.80	0.65	0.52	0.25	0.31	0.65	1.16	1.90
δ^{+}	0.71	0.45	0.52	0.25	0.29	0.45	1.27	1.92
δ^{-}	0.86	0.42	0.66	0.25	0.26	0.42	1.58	1.99
λ	1.90	1.90	0.97	0.50	0.84	1.90	2.95	3.00
φ	20.87	20.56	16.51	0.19	5.52	20.56	34.97	55.87

7.1.1 Utility Parameters under Risk

Recall from Chapter 3 that for the CPT model estimated in this thesis, the curvature of the value function is determined by α and β. Also in line with the definition of risk aversion/seeking in Chapter 2 in respect of the curvature of the value function; values of $0 < \alpha, \beta < 1$ implies risk aversion and risk seeking in the domains of gains and losses respectively. The parameter λ on the other hand symbolizes differences in the weight attached to loss compared to gain.

Figures 13 and 14 are plots showing the distribution of α and β parameters of the value function at individual level. Figure 13 shows that of the 158 participants, majority (over 72%) have $\alpha < 1$ parameter value. This indicates that the curvature of majority of the value function for gains was concave. Thus, in line with the definition adopted in section 2.1.1 in Chapter 2 describing risk aversion in respect of the curvature of the value function; farmers were prevalently risk averse in the gain domain (although to varying degrees as shown across the different percentiles in Table 14). The distribution of the value function for losses as presented in Figure 14 confirms that for about 54% of participants $\beta < 1$ implying a majority had convex value function in the loss domain and indicating predominantly risk seeking attitude towards losses.

Notably, the results in Table 14 and distributions in Figures 13 & 14 show that preferences of many respondents could only be modelled using "extreme curvature" of the value function. The masses clustered at the lower limit of the restriction for both α and β indicates extreme behaviour *i.e.* excessive risk aversion (as presented in the 50th percentile) and risk seeking in the gains and loss domains respectively, which is line with the findings reported in Chapter 6.

A one sample Wilcoxon Signed-Rank test show that the parameters α and β are significantly less than 1 at the 1% level (Z = -7.50, p < 0.001 and Z = -5.08, p < 0.001 respectively) thereby we reject the hypothesis of domain specific risk neutrality.

Hypothesis 1: Attitudes to risk depends on content domains

A Wilcoxon Signed-Rank test to compare sample distribution of α and β parameters shows statistically significant difference between α and β at the 1% level (Z = -3.16, p < 0.001) in which case the hypothesis that the sample distributions are equal *i.e.* α = β is rejected in favour of α < β. This significant difference denotes that the curvature of the value function is content domain specific. That is risk attitude is distinctive across gains and losses. This finding corroborates the results in Chapter 6. Past studies using CPT (including the pioneers Tversky & Kahneman, 1992) have reported similar findings.

Figure 13-18: Histogram of the CPT parameter for the beta distribution under risk

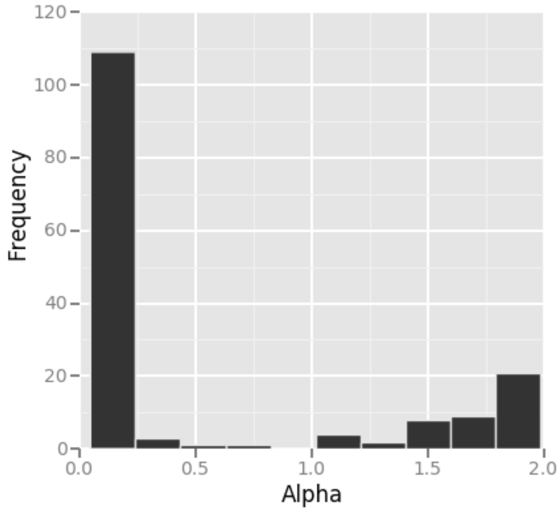


Figure 13. α parameter

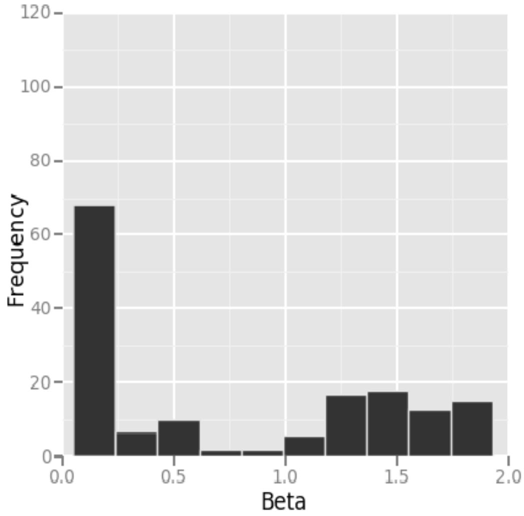


Figure 14. β parameter

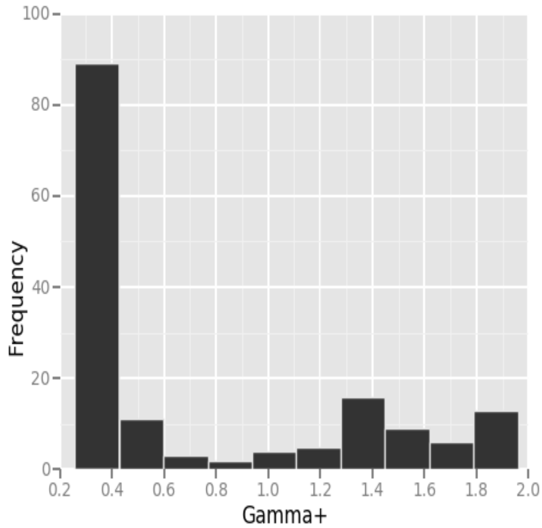


Figure 15. γ^{+} parameter

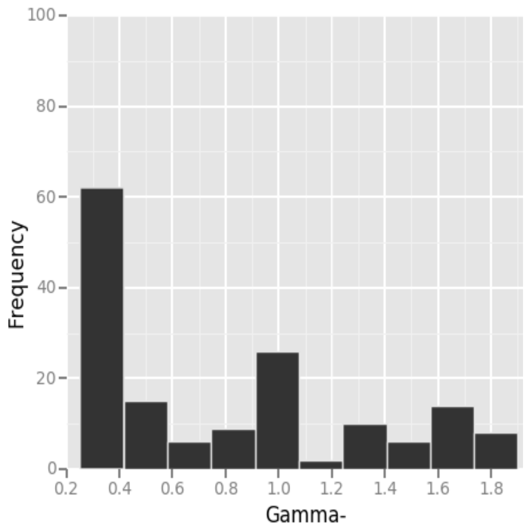


Figure 16. γ^{-} parameter

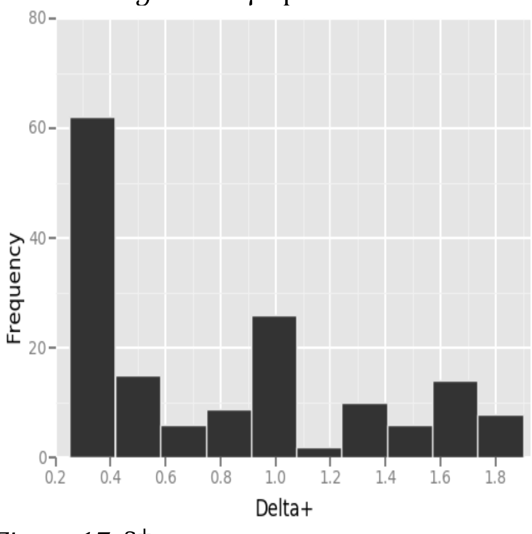


Figure 17. δ^{+} parameter

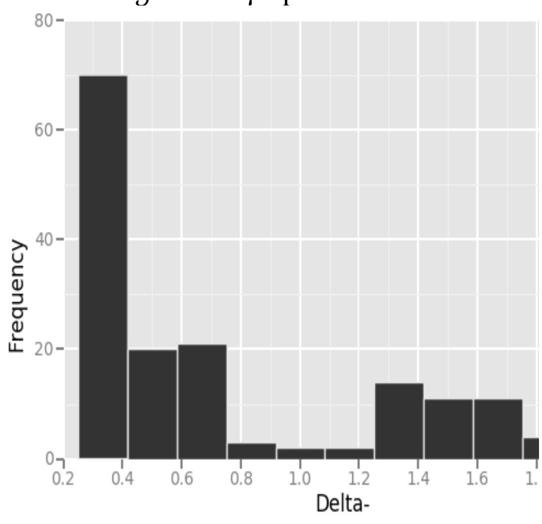


Figure 18. δ^{-} parameter

The coefficient of the DM's relative sensitivity to gain and loss (λ) show that participants with λ >1 made up over 64%. In aggregate, an estimated mean value for λ is 1.90 is obtained as shown in Table 14. This mean value reflects a kink that is not too sharp at the reference point. The mean coefficient (λ = 1.90) in this study is close to the value (λ = 1.87) reported in Booij and van de Kuilen (2007). However, as discussed in Balcombe *et al.* (2018), when a symmetry restriction is not imposed on the power parameters, the interpretation of this coefficient is complex.

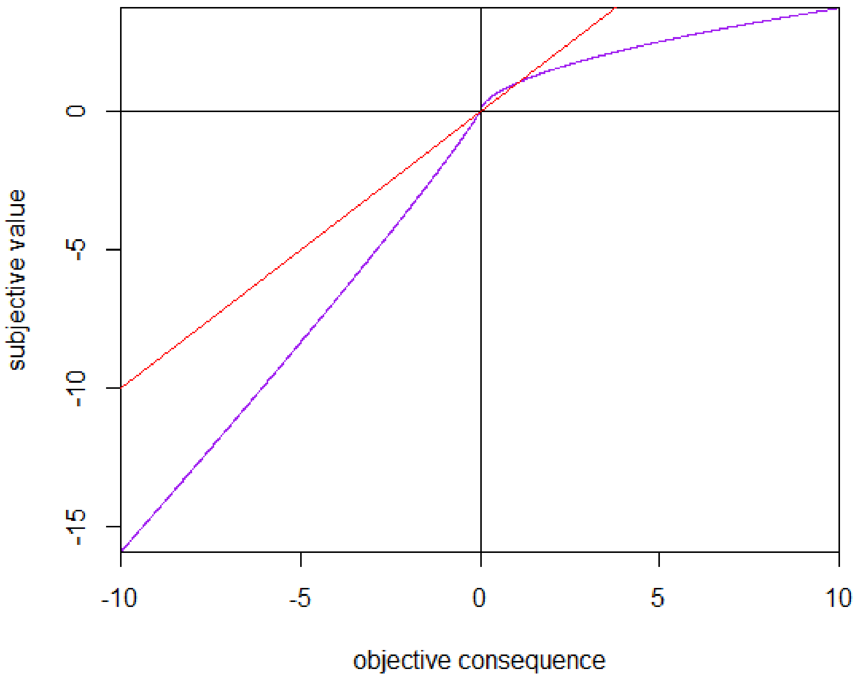


Figure 19. Average value function for α and *β* under risk.

Figure 19 is a plot of the results reported for the value function computed from the means of α, β and λ parameter estimates. As shown in the plot, the concavity for gains and convexity for losses is a pointer to risk aversion and risk seeking respectively and is in line with several previous findings of inverse *S*-shaped value function. Notably, the loss arm is steeper than the gains. This finding provides evidence in support of greater sensitivity to losses compared to gains; however not as intense as that reported in previous studies *e.g.* Tversky & Kahneman (1992) and Abdellaoui *et al.* (2007).

7.1.2 Probability Weighting Parameters under Risk

The distribution of the gamma parameter in the domains of gain γ^{+} and loss γ^{-} presented above in Figures 15 and 16 respectively shows that about 65% and 69% respectively fell within the group with $0 < \gamma^{+}, \gamma^{-} < 1$. This represents a predominant inverse *S*-shape for the parameters γ^{+} and γ^{-} which determines the curvature of the weighting function. That is, overweighting low probability and underweighting high probability. Further, a one sample Wilcoxon Signed-Rank test of the hypothesis that $\gamma^{+} = 1$ and $\gamma^{-} = 1$ provides the basis for rejecting the null hypothesis given the parameters are significantly less than 1 at the 1% level (Z = -5.24, p < 0.001 and Z = -4.87, p< 0.001). This finding is an indication of probability warping. This proof supports the hypothesis that that participants do warp probabilities and it corroborates Tversky & Kahneman, (1992); Mattos, Garcia & Pennings, (2007) that DM are sensitive to probability changes along the spectrum of unlikely to likely.

Although the mean and median of γ^{-} is arithmetically larger than γ^{+} as commonly reported in past studies[56], a Wilcoxon Signed-Rank test show that there is no significant statistical difference between γ^{+} and γ^{-} at the 5% level (Z = -1.29, p = 0.19). Thus the hypothesis that the sample distributions are equal *i.e.* $\gamma^{+} = \gamma^{-}$ cannot be rejected. This finding indicates that under risk, domain specificity have no significant effect on weights attached to events.

The weighting function parameters δ^{+} and δ^{-} which measures the level of optimism is presented in Figure 17 and 18. A significant proportion (consisting of about 70% and 63% respectively) of participants fell within the $0 < \delta < 1$ bracket. A one sample Wilcoxon Signed-Rank test show that the parameters δ^{+} and δ^{-} are significantly less than 1 at the 1% (Z = -6.19, p<0.001) and 5% (Z = -2.71, p=0.028) level respectively. This finding corresponds to the behaviour commonly reported in the literature as pessimism for gains and optimism for losses. On this basis, the hypothesis of a single but dominant risk attitude for gains and losses is rejected. This finding corroborates the hypothesis tested in Chapter 6.

[56] Glöckner & Pachur, (2012), Fox & Poldrack, (2008) are typical cases

A Wilcoxon Signed-Rank test used to compare sample distribution of the weighting parameter δ^{+} and δ^{-} show no significant statistical difference between δ^{+} and δ^{-} at the 5% level (Z = -1.29, p = 0.19). Thus, the hypothesis of similar elevation across domains cannot be rejected.

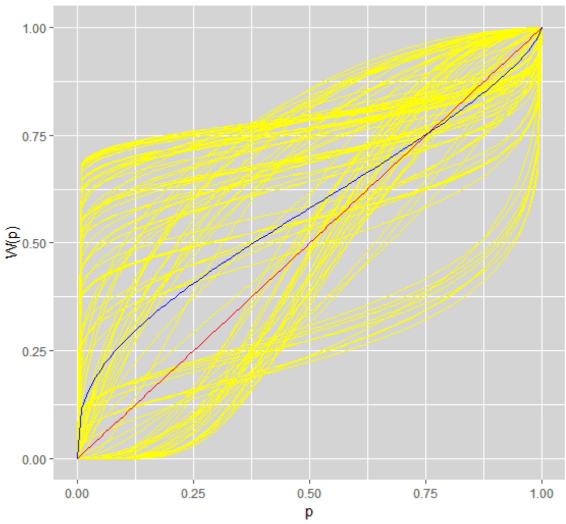


Figure 20. Prelec II probability weighting function for values $\boldsymbol{\gamma^{+}}$ **and** $\boldsymbol{\delta^{+}}$ under risk.

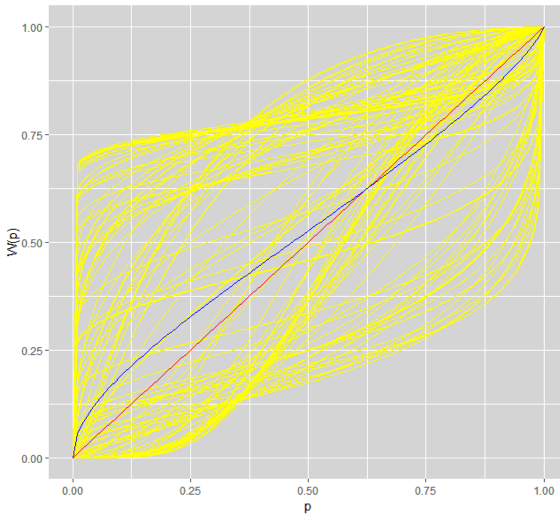


Figure 21. Prelec II probability weighting function for values $\boldsymbol{\gamma^{-}}$ **and** $\boldsymbol{\delta^{-}}$ under risk.

Note: The yellow lines in each plot represents the functions for individual DMs, the blue line shows the group-level mean, and the red line symbolizes the identity line

Figure 20 and 21 are plots of the probability weighting function for the parameters γ^{+}, δ^{+} and γ^{-}, δ^{-} respectively. The shape of the plots for the group-level mean confirms that on average the DMs overweighting of large probabilities in the gains domain is greater compared to loss. While both plots have an inverse S-shape however, there exists some difference in the weighting functions that arises from the inflection points and elevation in the gain domain relative to the loss domain.

Overall the attitudes to risk of farmers does not coincide with risk neutral EUT as the test of the various hypothesis ($\alpha = \beta = 1$; $\lambda = 1$; $\gamma^{+} = \gamma^{-} = 1$) earlier reported provide sufficient evidence to reject the EU maximizer hypothesis given the prevalence of outcome and probability sensitivity. However, the findings that farmers' did not regard equally likely outcomes as 'equally likely' contradicts the assertion of Levy & Levy (2002) that subjective probability warping does not feature in the case of equally likely outcomes.

7.1.3 Choice sensitivity

Recall that the estimated value of the choice sensitivity parameter φ determines whether the choice made by a DM is random or driven by subjective values. Typically, the smaller the value of the estimates of φ, the more random the decision and *vice versa*. An estimated mean (median) value for 20.87 (*resp*. 20.56) shown in Table 14 suggest that on average, participants choice pattern was influenced by the subjective valuations of prospects; indicating that participant choices where not utterly random.

7.2 Attitudes to Monetary Uncertainty

Similar to the model for risk, the uncertainty model was estimated with provision for different subjective value function for gains (α), losses (β), weighting function for gains ($\gamma^+$and δ^+) and losses ($\gamma^-$and δ^-). A description of the estimated parameters under risk is presented in Table 15**.** An observation of the results confirms heterogeneity among the respondents for all the parameters - a finding similar to the CPT estimation for risk.

Table 15
Descriptive Statistic for CPT Uncertainty Parameter under uncertainty

Variables	Mean	Median	SD	Min	25%	50%	75%	Max
α	0.57	0.09	0.72	0.05	0.05	0.09	1.20	1.97
β	0.93	0.86	0.82	0.05	0.06	0.86	1.83	1.99
γ^+	0.81	0.37	0.66	0.25	0.30	0.37	1.54	1.99
γ^-	1.15	1.10	0.75	0.25	0.28	1.10	1.97	2.00
δ^+	0.79	0.68	0.31	0.33	0.56	0.69	1.12	1.57
δ^-	0.94	0.68	0.68	0.25	0.26	0.68	1.65	1.97
λ	1.87	2.03	0.87	0.52	1.06	2.04	2.68	2.97
φ	13.78	6.18	13.69	0.17	1.31	6.18	30.87	41.89

7.2.1 Utility Parameters under Uncertainty

An examination of the distribution of the α and β parameter values predicted at individual level by the CPT model is presented in Figure 22 and 23. The majority of the participants accounting for over 75% had α < 1 parameter values implying concave curvature of the value function for gains. However, for the β parameter this was much less, as about 53% of the estimated value parameter for losses conformed to β < 1. This pattern is similar to the findings in the monetary risk domain where participants were predominantly risk averse for gains and risk seeking for losses.

Similar to the results reported in Chapter 6, the preferences of many respondents could only be modelled using extreme curvature of the value function. There are masses clustered at the lower limit of the restriction for both α and β*.* A large proportion of participants were excessively risk averse in the gain domains and risk seeking in the loss domain evident from the 50th percentile in Table 15 and distribution in Figures 22 & 23.

Figure 22-27: Histogram of the CPT parameter for the beta distributions under uncertainty.

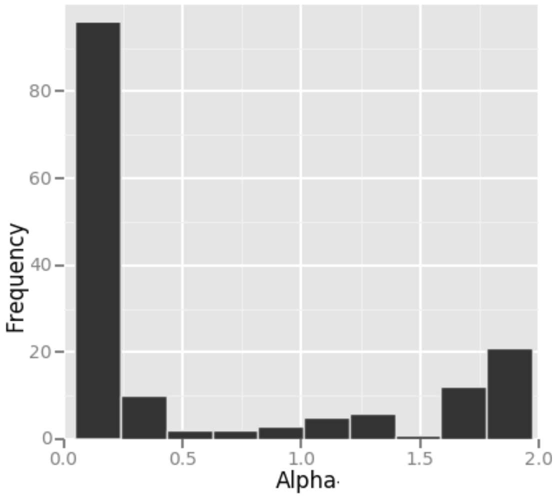


Figure 22. **α** parameter

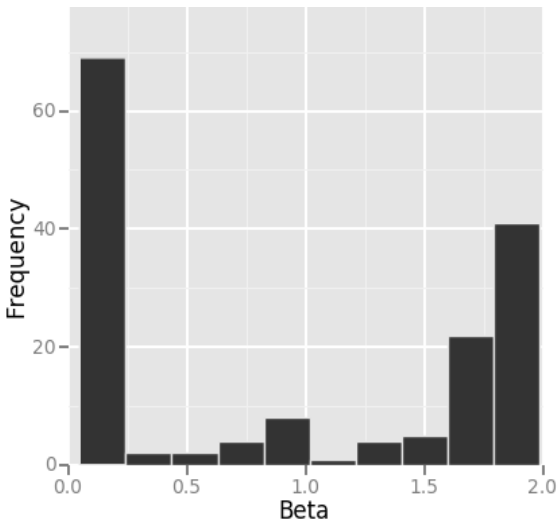


Figure 23. β parameter

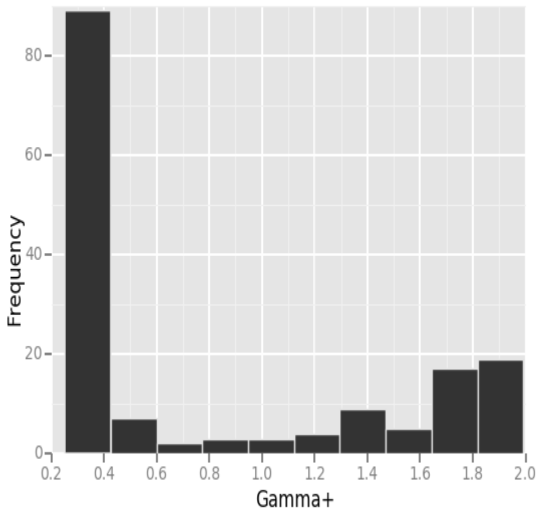


Figure 24. γ^{+} parameter

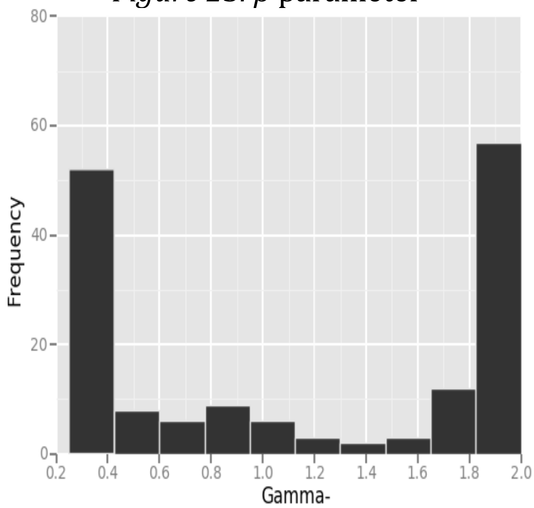


Figure 25. γ^{-} parameter

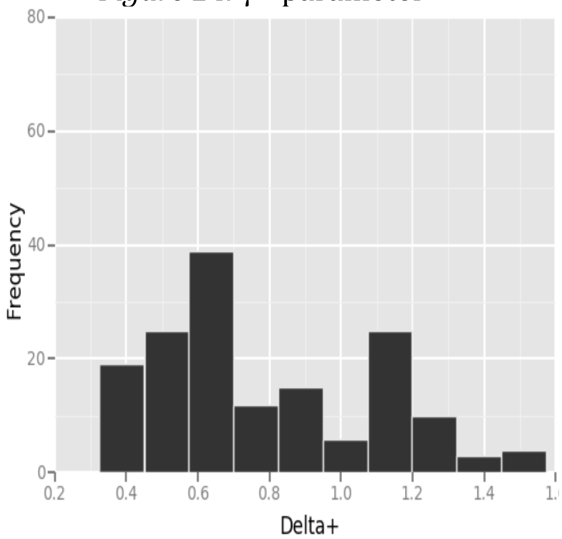


Figure 26. δ^{+} parameter

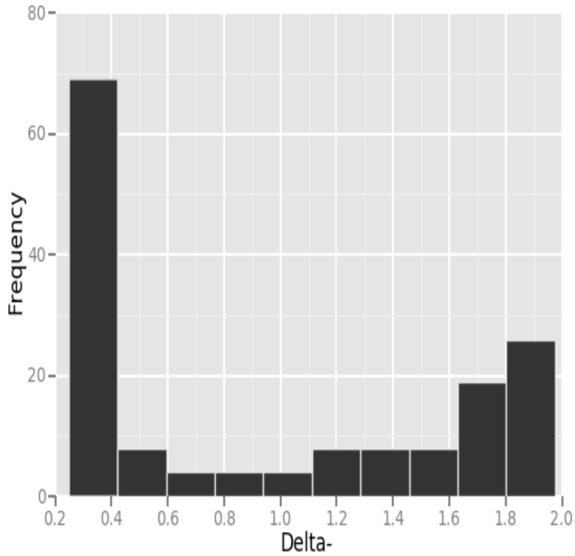


Figure 27. δ^{-} parameter

In aggregate, the results presented in Table 15 show the median (mean) value for α is 0.09 (0.57) and β is 0.86 (0.93). A one sample Wilcoxon Signed-Rank test show that the parameters α is significantly less than 1 at the 1% level (Z = -7.20, p < 0.001) thus the hypothesis α = 1 implying risk neutrality or linear sensitivity to outcomes in the gain domain is rejected. Similarly, the hypothesis that β = 1 is rejected at the 1% level (Z = -3.13, p < 0.001).

Hypothesis 2: Attitudes to uncertainty depends on content domains

In other to test the hypothesis that α = β, a Wilcoxon Signed-Rank test was used to compare sample distribution of α and β parameters. The result shows statistically significant mean difference between α and β at the 1% level (Z = 3.23, p < 0.001). This implies that under uncertainty the curvature of the value function is domain specific and is asymmetric across gains and losses thus rejecting the hypothesis that attitudes to uncertainty does not depends on content domains (α = β) and conclude that the alternative hypothesis is true at 95% confidence level.

The distribution of the coefficient of the DM's relative sensitivity to gain and loss (λ) show that participants with λ >1 made up over 72%. This proportion suggest that majority of farmers were more sensitive to losses than they are to gains of equal proportion. On average, the value for the estimated λ is 1.89 (with a median value of 2.03) as shown in Table 15. The above interpretation of λ are purely descriptive as in line with Balcombe *et al.* (2018), when a symmetry restriction is not imposed on the power parameters, the interpretation of this coefficient is complex.

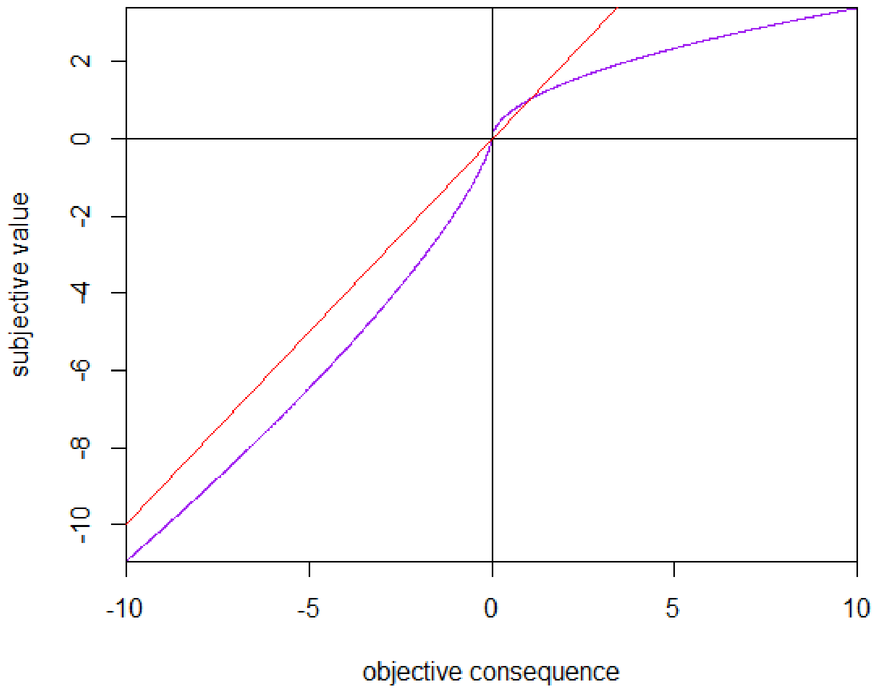


Figure 28. Average value function for α and *β* under Uncertainty.

Figure 28 shows the value function computed from the average parameter values of α, β and λ parameter estimates. As shown in the plot, the concavity for gains and convexity for losses is an indication of risk aversion and risk seeking respectively. Notably, the loss region is steeper than the gains region with a kink that is not too sharp at the reference point. Again, this finding provides evidence in line with several previous findings that reported inverse *S*-shaped value function.

7.2.2 Probability Weighting Parameters under Uncertainty

Figures 24 and 25 are plots of the distribution of γ^{+} and γ^{-} parameters under uncertainty. Inverse *S*-shape ($0 < \gamma^{+} < 1$) was predominantly observed across DMs for the gain parameters γ^{+} while *S*-shape ($\gamma^{-} > 1$) was most prevalent for losses given the proportion of 63% and 51% having the aforementioned shapes for gain and loss respectively. This result differs from the inverse *S*-shape for both γ^{+} and γ^{-} shown by participants under risk. This inverse S-shape (*S*-shape) implies overestimation (underestimation) of low probabilities and underestimation (overestimation) of high probabilities for gain (loss).

Using Wilcoxon Signed-Rank test, the hypothesis that $\gamma^{+} = 1$ and $\gamma^{-} = 1$ is rejected given the γ^{+} parameter is significantly less than 1 and the γ^{-} is significantly greater than 1 at the 1% a ($Z = -3.11$, $p < 0.001$; $Z = -3.94$, $p < 0.001$ respectively). This pattern is an evidence of probability warping.

Aggregate level predictions of the estimation of the gamma parameter for the beta distribution that characterise gain γ^{+} and loss γ^{-} are presented in Table 12. The statistics show a median value of 0.37 for $\gamma^{+}$and 1.10 for γ^{-}. A Wilcoxon Signed-Rank test used to compare sample distribution of the weighting parameter γ^{+} and γ^{-} suggest significant statistical difference between γ^{+} and γ^{-} at the 1% level ($Z = -3.54$, $p < 0.001$). Therefore, the hypothesis that $\gamma^{+} = \gamma^{-}$ is rejected. This finding is different from what was obtained under risk and favours the suggestion that under uncertainty, the weights attached to probabilities depend on content domain.

Figure 26 and 27 are plots of the distribution of the weighting function parameters δ^{+} and δ^{-}which defines the degree of elevation of the PWF and the attractiveness of the prospects. The plots confirm that a large proportion (consisting of about 70% and 63% respectively) of participants fell within the $0 < \delta < 1$ bracket. A one sample Wilcoxon Signed-Rank test show that the parameters δ^{+} is significantly less than 1 at the 1% level ($Z = -7.06$, $p < 0.001$). However for δ^{-}, the hypothesis that and $\delta^{-}=1$ cannot be rejected ($Z = -0.63$, $p = 0.26$). This finding corresponds to pessimism for gains and (near) neutrality for losses. As such, the hypothesis of a single but dominant attitude for both gains and losses is rejected.

The elevation parameters δ^+ had a median (mean) of 0.68 (0.79) while the elevation parameters δ^- had a median (mean) of 0.68 (0.94). A Wilcoxon Signed-Rank test used to compare sample distribution of the weighting parameter γ^+ and γ^- suggest significant statistical difference between γ^+ and γ^- at the 5% level (Z = -2.12, p = 0.03). Thus, the hypothesis of identical elevation across domains is rejected and conclude that the hypothesis of difference in elevation of the weighting function for losses than for gains is true at 95% confidence level.

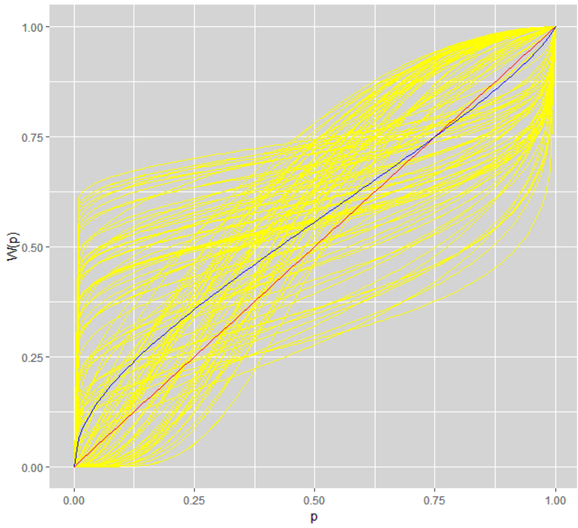


Figure 29. Probability weighting function for values $\boldsymbol{\gamma^+}$ **and** $\boldsymbol{\delta^+}$ under Uncertainty

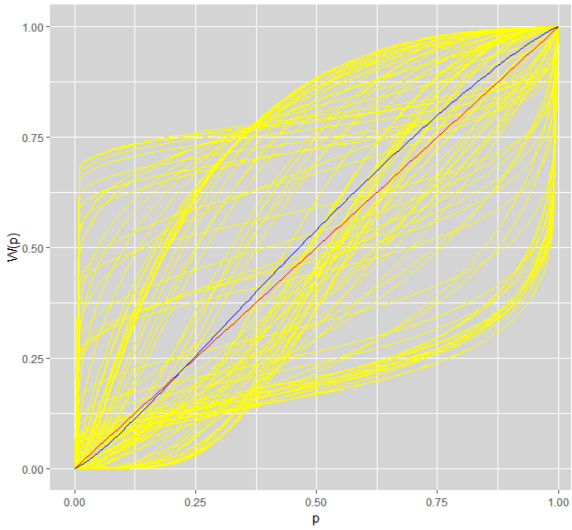


Figure 30. Probability weighting function for values $\boldsymbol{\gamma^-}$ **and** $\boldsymbol{\delta^-}$ under Uncertainty

Recall: The yellow lines in each plot represents the functions for individual DMs, the blue line shows the group-level mean, and the red line symbolizes the identity line

The probability weighting function for values γ^+, δ^+ and γ^-, δ^- are presented in Figure 29 and 30. The shape of the group-level mean plots confirms an inverse *S*-shape for gains and *S*-shape for losses suggesting that the DMs underweights large probabilities for gain but overweights large probabilities of loss. Other difference in the weighting functions is notable in the inflection points and elevation for in the gain domain relative to the loss domain.

Overall, the behaviour of farmers does not coincide with EUT as the test of the various hypothesis ($\alpha = \beta = 1$; $\lambda = 1$; $\gamma^+ = \gamma^- = 1$) earlier reported provide reason to reject the EU maximizer hypothesis at 95% confidence level given that outcome and probability sensitivity are observed.

7.2.3 Choice sensitivity

As discussed in the previous section that the estimated value of the choice sensitivity parameter φ determines if the choice made by a DM is random or driven by subjective values. Smaller values of the estimates of φ imply randomness in the decision and vice versa. An estimated mean (median) value for 13.7 (6.18) shown in Table 15 suggest that participant choices where not utterly random but determined by the subjective values. However, comparing the result to that of risk however, participants made less random choices on average under risk than uncertainty as expected *a priori*.

Unlike the Mean-Standard deviation estimation in Chapter 6 where it is assumed participants exclusively evaluate specific properties of the distribution such as the mean and standard deviation; on the contrary the CPT parameter estimation indicated that participants possibly made decisions by means of putting into operation an intricate weighting of outcomes across the distribution. One postulation is that participants inferred correspondence between the two prospects and possibly mapped values across prospect which translates to some form of ranking.

Also, despite using continuous prospects; respondents did not treat equally likely outcomes as 'equally likely' and appear to demonstrate cumulative probability distribution warping consistent with the Cumulative Prospect Theory (CPT).

7.3 Comparing Risk and Uncertainty Attitudes

The different (combinations of) shapes of α and β parameters demonstrate that risk and uncertainty attitude are not homogenous among farmers. By grouping participants according to the shape of their value function[57] for both gains and losses under risk as shown in Figure 31, the largest proportion of participants (about 58%) had concave (convex) value function for gain (loss) followed by (about 55%) concave value function in both gain and loss domains. This finding corroborates the results of Resende & Tecles, (2011)[58].

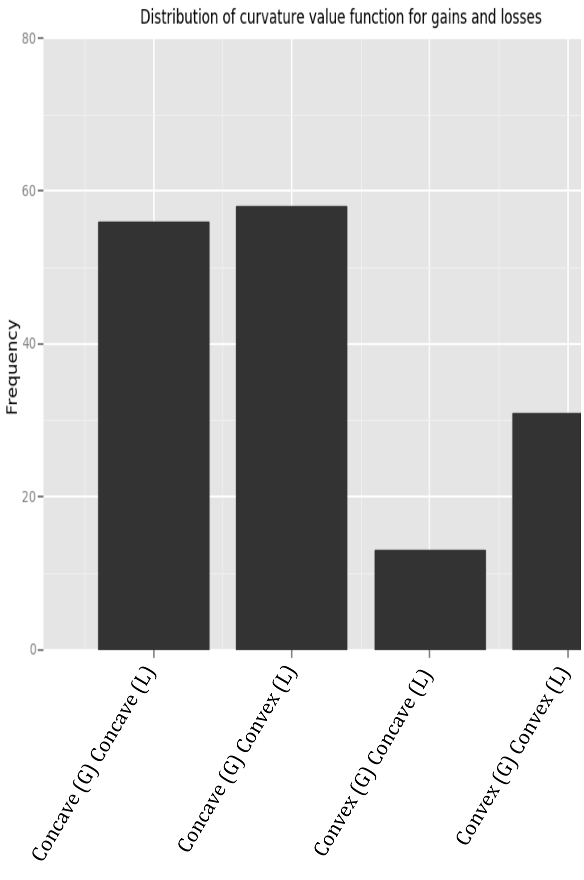


Figure 31. Shape of the value function for gains and losses under risk

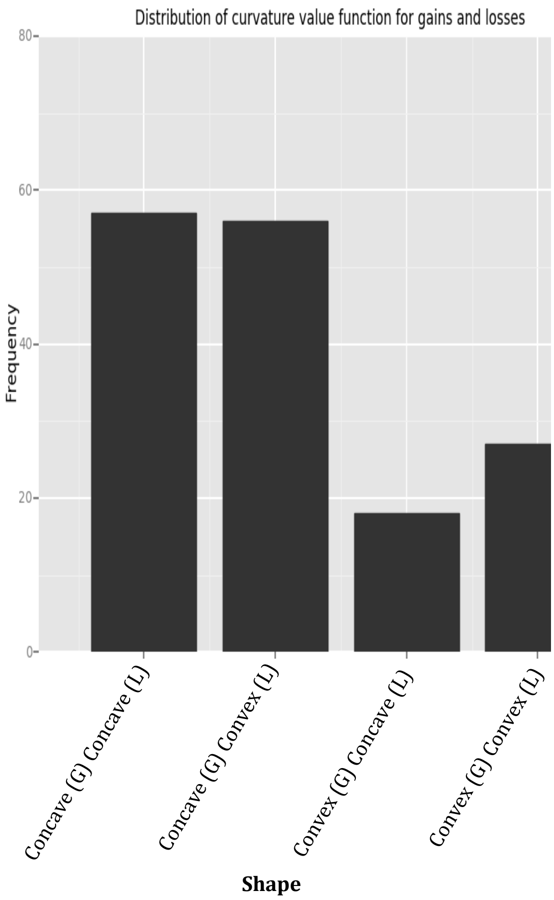


Figure 32. Shape of the value function for gains and losses under Uncertainty

***Concave (G)** = Concave in gain domain, **Concave (L)** = Concave in loss domain, **Convex (G)** = Convex in gain domain & **Convex (L)** = Convex in loss domain*

[57] Participants are distributed according to the shape of the value function jointly considering the shape of α and corresponding β.

[58] Resende & Tecles, (2011) reports concavity in both gain and loss domains however they point out that in their case, concave utility suggest but did not directly express risk aversion

However, under uncertainty this pattern is different as presented in Figure 32. The predominant pattern was concave α and β followed by concave (convex) value function for gain (loss). Abdellaoui & Kemel, (2013) obtained similar pattern of predominant concavity for both gains and losses followed by concavity for gains and convexity for losses *albeit* under risk.

Hypothesis 4: Attitudes to risk and uncertainty differ within context domain

A Wilcoxon Signed-Rank test to compare sample distribution of α's for risk and uncertainty shows no statistically significant difference between α's under risk and uncertainty at the 5% level (Z = -1.57, p = 0.11) in which case the hypothesis that the sample distributions are equal cannot be rejected. On the other hand, a Wilcoxon Signed-Rank test to compare sample distribution of β's for risk and uncertainty shows statistically significant difference between β's under risk and uncertainty at the 5% level (Z = -2.19, p = 0.02). This, significant difference denotes that the distribution of the curvature of the value function within a specific context (loss domain in this case) depends on conditions (risk *vs* uncertainty) and corroborates the results reported in Chapter 6.

Taken together on average however, farmers are risk averse for gains and risk seeking for losses under both risk and uncertainty. Specifically, the study finds evidence of a gain-loss asymmetry in the utility function parameters. While the shape of the gain arm of the value function under risk and uncertainty appears similar at aggregate level, the loss arm under risk was more convex (indicating higher risk seeking for losses) compared to uncertainty.

Overall, there is sufficient reason to dispute linear probability weighting both for risk as well as for uncertainty since the results provide evidence of probability weighting for gains and losses. However, the weighting pattern is different across risk and uncertainty. While participants overweight low probabilities for gains and losses on average under risk, for uncertainty overweighting of small probabilities did not apply to losses. As expected *a-priori*, a comparison of the structural "noise" parameter (μ) of risk and uncertainty shows that choices made under risk were less random than under uncertainty and the mean differences were statistically significant.

Although on average while the estimated parameters (α, β, λ , γ^+, γ^-, δ^+, δ^-, μ) for risk and uncertainty appear similar, however overall there is weak (though significantly positive) correlation between these parameters across risk and uncertainty as shown in Figure 33(A-G).

Figure 33(A-G). Scatterplots for the association between value and probability weighting parameters under conditions of risk *vs*. uncertainty.

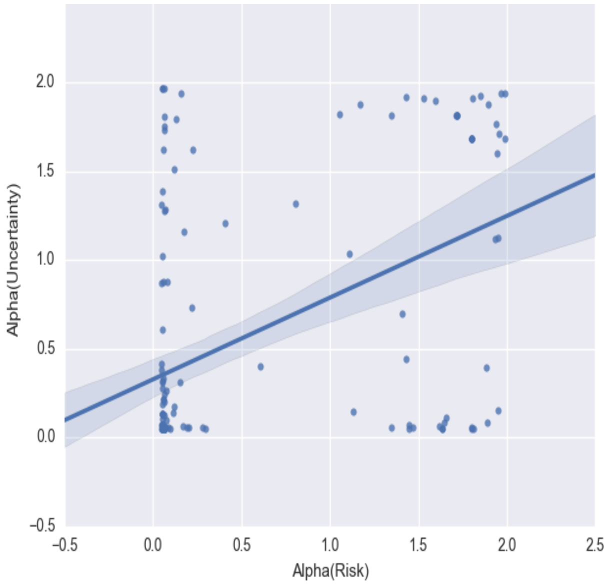


Figure 33A. Association between α value for risk and uncertainty.

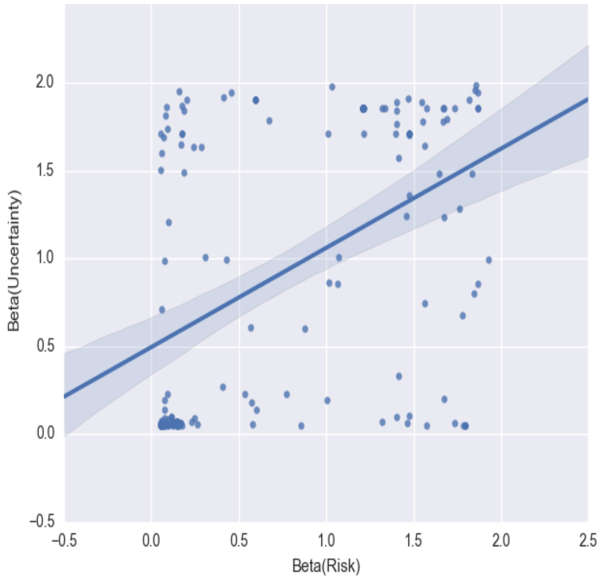


Figure 33B. Association between β value for risk and uncertainty.

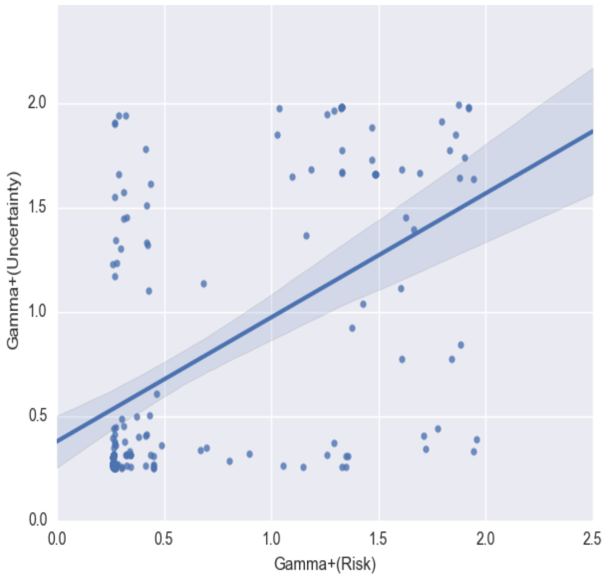


Figure 33C. Association between γ^+ value for risk and uncertainty.

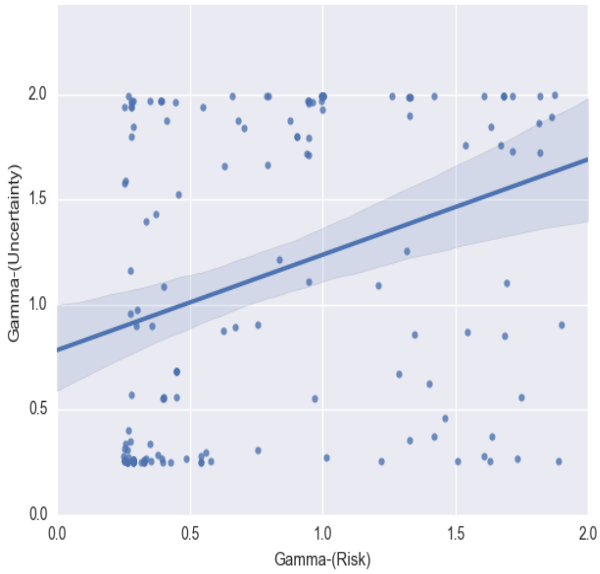


Figure 33D. Association between γ^- value for risk and uncertainty.

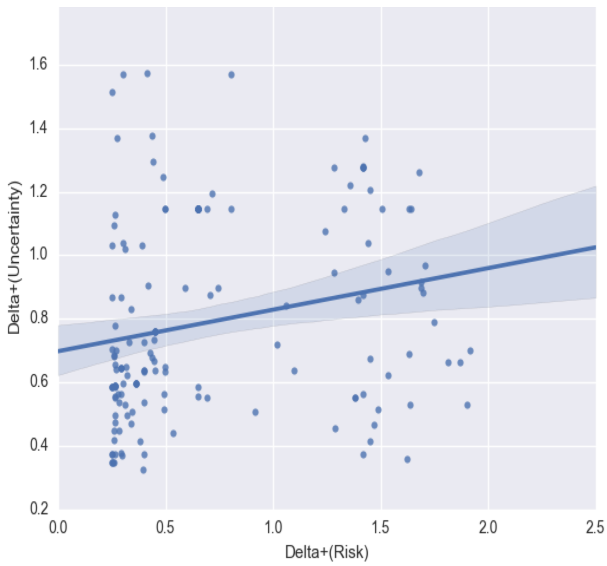


Figure 33E. Association between δ^+ value for risk and uncertainty.

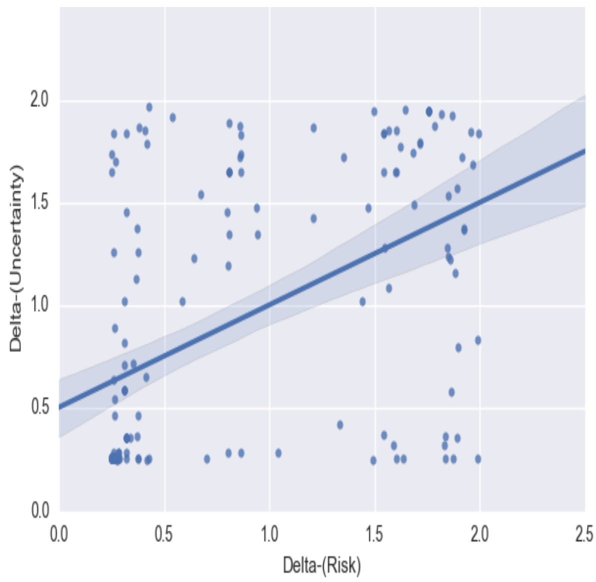


Figure 33F. Association between δ^+ value for risk and uncertainty.

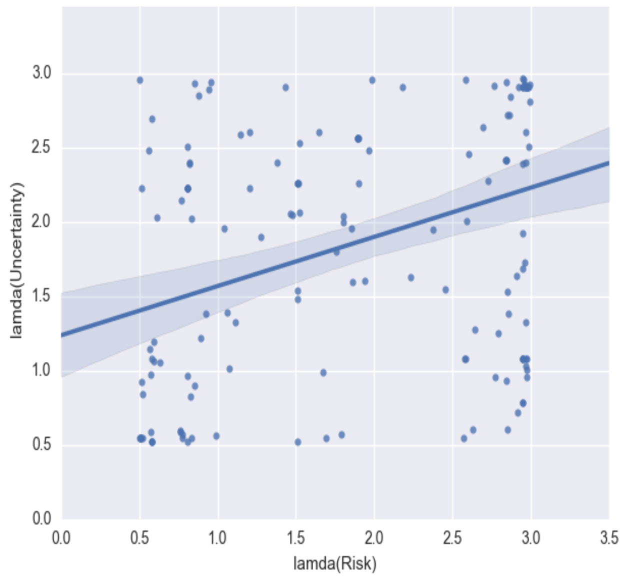


Figure 33G. Association between λ value for risk and uncertainty.

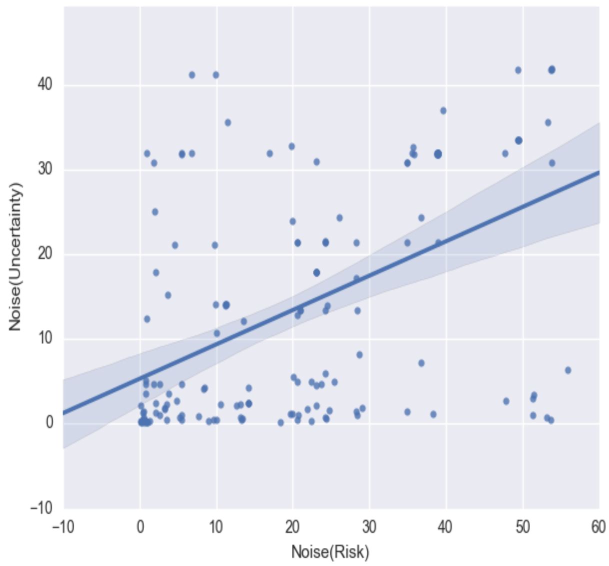


Figure 33H. Association between μ value for risk and uncertainty.

Two arguments are put forward to explain the observed differences between the risk and uncertainty parameter estimates. First, there may well be genuine differences in individual behaviour under risk and uncertainty among the participants. Acknowledging the distinction between conditions of risk and uncertainty, a rational choice under risk may not necessarily be the same under uncertainty. This does not suggest that DMs are incoherent but given different conditions, DMs may act differently. Second, the different parameter values obtained under risk and uncertainty for the same participant (for instance the characterisation of an individual whose choice follows a sequence of say inner-outer-inner under risk *versus* inner-outer-inner under uncertainty results in different CPT parameter values), could possibly have arisen from estimating the CPT parameters under mis-specified model. By forcing the model unto the data that is inconsistent with the model create dependence on the parameter values which otherwise should not arise in a true model.

Crucially, some of the findings in this study raises concerns about the CPT model as it may not have sufficient descriptive strength required to explain all participants' attitudes. First, at the individual level, there is much heterogeneity in the behaviour and average behaviour is not supported by individual behaviour. Second, the standard CPT function struggled to deal with certain behaviour (including phenomenon of *negligible gain avoidance* and *negligible loss seeking* and significant number of non-switching at different points in risk preference ladder) highlighted in Chapters 5 and 6 evident from the significant bunching of individuals at the end of the parameter space. Thus, the preferences of many respondents could only be modelled using "extreme curvature" of the value function.

Although the CPT provides a useful method to characterize heterogeneity however, relying on the CPT alone to draw conclusions especially for evidence-based recommendations in the face of the aforementioned concerns is limiting. This deduction is in line with the conclusion of previous studies including Harrison & Swarthout (2016) and Bruhin, Fehr-Duda & Epper (2010). Therefore, the Chapter 8 examines the data in the light of other decision theories.

7.4 Summary

In summary, Chapter 7 covers results obtained from estimating parameters of the Hierarchical Bayesian CPT model. The CPT analysis in this chapter was constrained to the two most important cases (monetary risk and uncertainty). Although the estimates of the individual parameters were derived from a Bayesian procedure, inference about the parameters was by classical tests applied to the parameters extracted from the Bayesian mixed logit.

Key findings are that attitudes differ under the different conditions (risk and uncertainty) and content (gain, loss and mixed) domains. Using continuous prospects, respondents did not treat equally likely outcomes as 'equally likely' and appear to demonstrate cumulative probability distribution warping consistent with the Cumulative Prospect Theory (CPT). In aggregate however, farmers are risk averse for gains and risk seeking for losses under both risk and uncertainty. However, there is reason to doubt the adequacy of the CPT model to handle the data in this case since the preferences of many respondents could only be modelled using "extreme curvature" of the value function. This was induced by *"negligible gain avoidance"* (*i.e.* avoiding prospects with zero lower bound in the gain domain) or *"negligible loss seeking"* (*i.e.* preferring prospects with zero upper bound in the loss domain) behaviours. The behaviours were bound to be reflected in this way under the CPT as the aforementioned phenomenon and the significantly large number of non-switching at different points in risk preference ladder resulted in bunching of individuals at the end of the parameter space.

Arguably, the CPT model may not be the most appropriate to be applied in this context since the extreme parameter values are detrimental for model prediction accuracy and limits the capability of the CPT to effectively describe participants' behaviour. However, it serves as a good basis for describing how DM's decision makers act. Alternatives theories that may rationalize the NGA and NLS phenomenon are explored in Chapters 8.

Chapter 8

Alternative Explanatory Theories - Results and Discussions

8.0 Introduction

The results in Chapter 7 indicates that the attitude to risk and uncertainty cannot be entirely justified by the EUT, as there is empirical evidence of probability warping. Similarly, the CPT does not fit the data sufficiently from the perspectives of modelling participants' attitudes; as many respondents could only be modelled using extreme curvature of the value function. The CPT also struggled to deal with the behaviour highlighted in the previous sections.

Chapter 8 examined decision rules and alternative theories with the aim of providing further explanation to the findings in previous Chapters. It pivots on testing the proposition that '*NGA'* and '*NLS'* are nothing more than artefact of the design. In addition, it examines a different perspective that it could be that participants may have adopted different decision rules which may well reflect those used in participants' day-to-day decision-making.

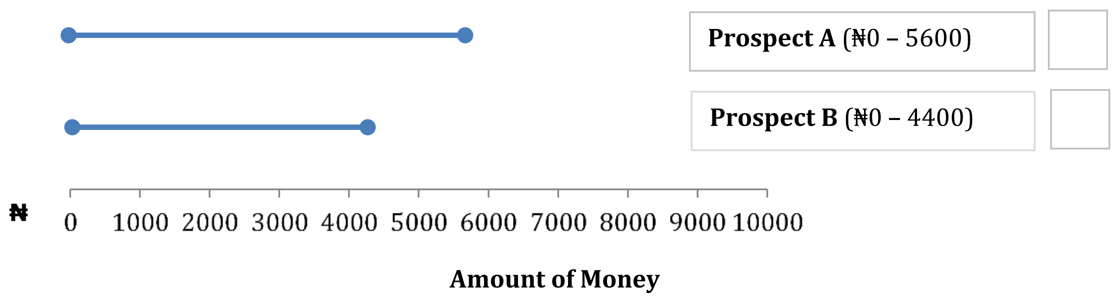
The sequence of discourse in Chapter 8 is as follows. Section 8.1 examines participants' level of comprehension 8.2 presents results of selected heuristics and decision rules, section 8.3 discusses findings from salience theory while sections 8.4 examines the role of zero avoidance in participants' decision.

8.1 Evaluating Participants' Comprehension

As pointed out in Chapter 6, this section investigates the possibility that the phenomenon of '*negligible gain avoidance'* and '*negligible loss seeking*' could be nothing more than artefact of the design. Participants understanding of the experiment was tested before and after the experiment. As discussed in section 5.2 in Chapter 5, at the beginning of the experiments a detailed explanation of the necessary concepts relating to the choice task were explained using an unbiased spinner and demonstration continued until participants showed complete understanding of the concepts. Thereafter, four trial choice tasks preceded the actual experiment to test respondents' understanding. With the onset of a new set of choice tasks such as - risk to uncertainty or from gains to losses, respondents attention were drawn by the researcher and necessary explanations made.

Post-experiment, each farmer participated in a follow-up experiment. However, unlike the main experiment, the prospects pair presented to each participant consisted of '*biased'* and '*stochastically dominated'* prospects. The prospect pairs were designed such that Prospect A has a likelihood of the best outcome on the upside and was at least as good as prospect B on the downside, so that a rational DM is expected to pick Prospect A. The need for this section of experiment was to test whether level of understanding of the experiment affected participants' risk seeking or risk avoidance attitude as well as influenced the phenomenon of '*negligible gain avoidance'* and '*negligible loss seeking'*. An example of the experiment[59] presented to participant is presented in Figure 34.

[59] Details of the experiment is reported in Appendix 3.



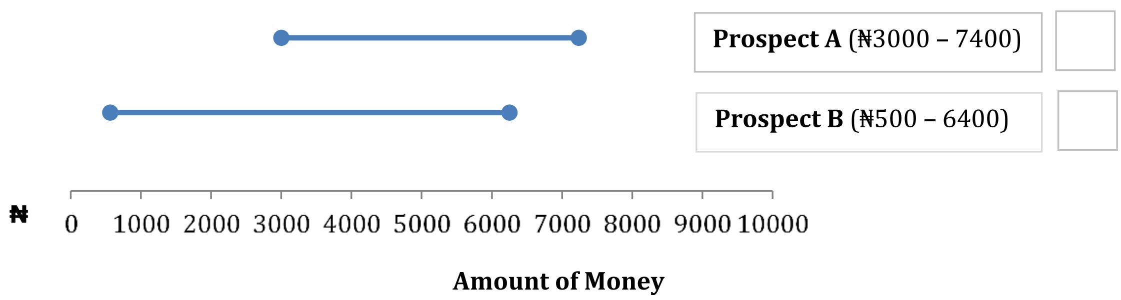


Figure 34a. Examples of '*stochastically dominated'* prospects in gain domain

Since Prospect A dominates B, a rational participant would avoid B. This *a-priori* expectation is met as the result show that no participant (0%) picked any stochastically dominated prospect. This finding suggests that is not simply a deficient level of understanding of the experiment that has led to what we have termed '*negligible gain avoidance'* and '*negligible loss seeking'*.

Further, participants were given experiments which were flipped version of the main experiment *as* shown in Figure 34b. In this case, Prospect B was more 'risky' in terms of wider variance. *A-priori* it was expected that participants choices would be consistent such that those participants that chose Prospect A in the main experiment should choose prospect B in the follow-up.

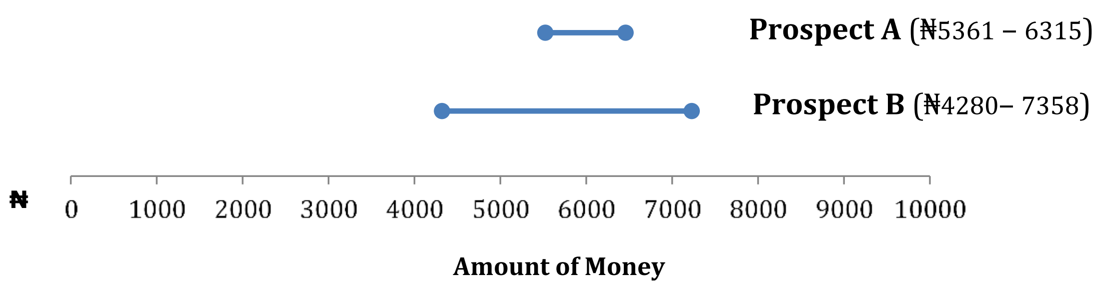


Figure 34b. Examples of '*flipped'* version of prospects in gain domain

The results presented in Figure 35 indicates that all participants' (100%) in the loss domain under risk made consistent choices when presented with the flipped lotteries.

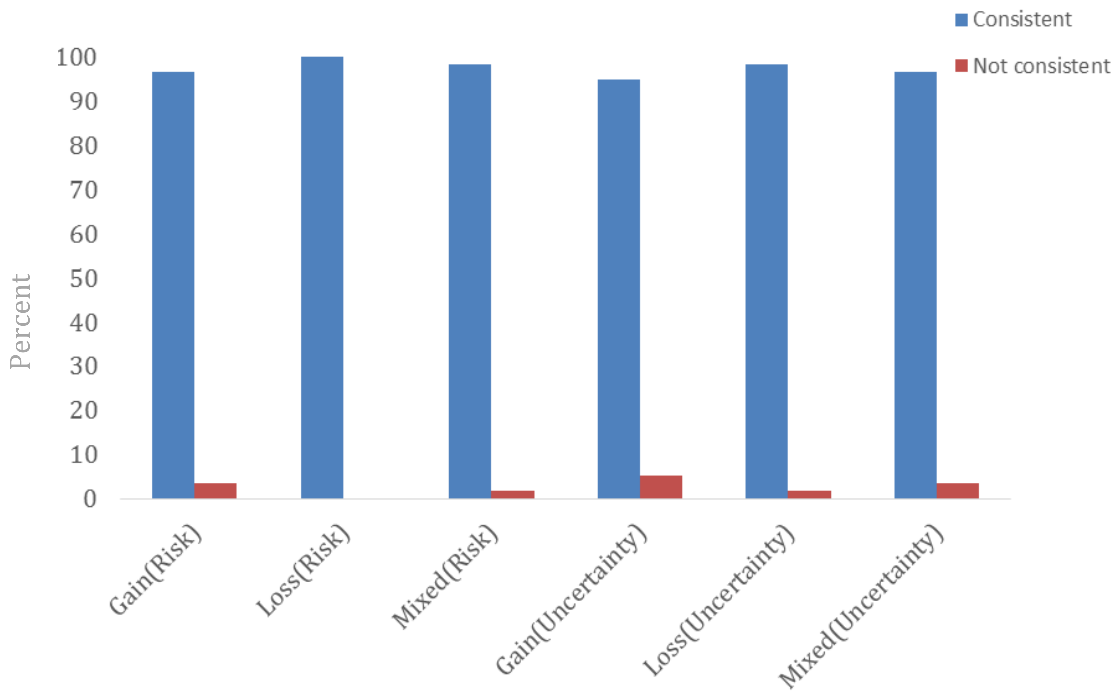


Figure 35. Histogram showing participants' switching across domains

Across other domains however, about than 5% made inconsistent choices in the gain domain under uncertainty while about 2% of participants were inconsistent in their choices in the gain domain under risk. This result subjected to a paired sample t-test show no statistical significant difference in the choices made during the experiment and post-experiment under conditions of risk (t = -0.81, p > 0.41) and uncertainty (t = 0.70, p > 0.47) at the 10% level. This finding again suggest that participants' understood the experiment and their decisions where not merely artefact of the experiment design.

8.2 Selected Heuristics and Decision Rules

In Figures 36 and 37, the proportion of choices under risk and uncertainty that conforms with the prediction of maximin and maximax is presented. As discussed in section 3.6 in Chapter 3, using the maximax criterion; the DM assesses prospects based on the highest payoff possible. The DM's aim is to maximize the maximum payoff. The sequence of decision-making involves isolating the maximum payoff of all available options then choosing the option with the highest maximum payoff. On the other hand, in the case of maximin; the DM is most concerned with avoiding the worst possible outcome of the worst-case scenario with the belief that the chance that the worst case in any event will happen is high. Thus, the DM identifies the worst possible outcomes then choose the option that is best among the worst.

Under risk (uncertainty *respectively*) in the gain domain, the choices made by about 65% (67%) conforms with the expectations of minimax heuristic. Similarly, in the mixed domain under risk and uncertainty about 56% and 59.1% of choices respectively coincides with the predictions of the minimax heuristic. For the loss domain however, the predominant heuristic was the maximax heuristic as 56% and 59% of the choices made under risk and uncertainty respectively was in line with maximax heuristic prediction.

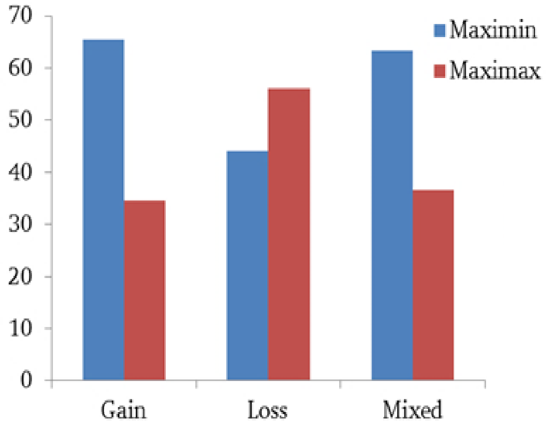


Figure 36. Proportion of choices under risk similar to the prediction of maximin and maximax

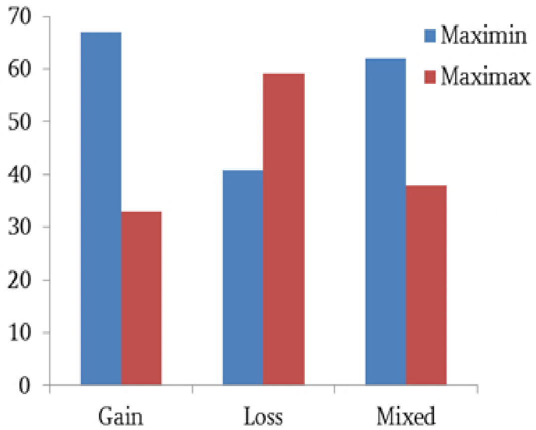


Figure 37. Proportion of choices under uncertainty similar to the prediction of maximin and maximax

An asymptotic McNemar's test confirmed that in the gain domain there is statistically significant differences between the proportion of choices made by participants' and the prediction of the maximin $\chi = 534$, $p < .001$ (*resp*. maximax $\chi = 1033$, $p < .001$). Similarly in the loss domain there is statistically significant differences between the proportion of choices taken by participants' and the predictions of the maximin $\chi = 693$, $p < .001$ (*resp*. maximin $\chi = 883$, $p < .001$). Finally in the mixed domain, the test for statistically significant differences between the proportion of choices made by participants and the prediction of the maximin also suggest that there is statistically significant $\chi = 856$, $p < .001$ (*resp*. maximax $\chi = 1501$, $p < .001$). The implication for this finding is that although certain proportion of the sample choices conforms to maximin and minimax predictions, this is not statistically sufficient to conclude that the maximin and minimax heuristic predicts the predominant choices overall.

8.3 Salience Theory

This section briefly examines the possibilities of participants allotting weight to judgments for salient payoffs. As discussed in section 3.8 of Chapter 3 salience is determined through a function that examines the similarities and differences of the characteristic of prospects in respect of a reference level with the aim of ascertaining the extent to which that characteristic is distinctive and attracts the DM's attention. Specifically, this section sought to provide answers to the questions; are zero payoffs salient? If yes, was it overweighted?

Recall from the discussion in Chapter 3 that the CPT overweight tail events *i.e.* attaching more weights to outcomes that are unlikely or events that are rare. However, Salience theory suggest that the differences in payoffs is key to weighting payoffs. Thus only when the greatest difference is salient are tail events then overweighted.

There are two main assumptions regarding the densities that could be made herein. First, complete independence between prospects. Second, participants' may have inferred correspondence between the two prospects and possibly mapped values across prospect such that for every value in Prospect A, there is an equivalent value in B which translates to some form of ranking and correspondence between both prospect. The certainty equivalent under salience with power utility for these two assumptions was estimated.

By treating the lotteries as discrete uniform lotteries with 1000 increments between the upper and lower limits' approximating the continuous case was possible. For the assumptions of complete independence and correlation, the baseline parameter values from Bordalo *et al.,* (2012) was adopted where θ = 0.1, δ = 0.7 and a power utility coefficient α = 0.25. Recall that θ > 0, permits for the possibility of prospects with zero payoffs to be less salient than non-zero payoffs provided there is sufficient distance between payoffs of one prospect and its alternative. It was expected *a-priori* for instance in the gain domain where the lower bound of the 'risky' prospect is more salient, the DM would avoid taking risk *i.e.* the salience of the worst payoff will result in the risky prospect appearing less attractive.

The results however provides evidence to conclude that salience does not explain participants' zero averse/liking. Notably, for those prospects with zero bounds, salience theory suggest that it may not have been the zero payoff that resulted in '*negligible gain avoidance'* or '*negligible loss seeking'* but some of the other payoff values may have been extremely salient. Changing the values of θ and δ parameters did not change the results much; thereby suggesting minimal sensitivity to the θ and δ values. Although participants may have put some additional weights to salient payoffs, however the extent to which it is overweighted is not determined and it may well differ across participants. Crucially, it gives an indication that salience however can result in participants, making 'unusual' choices.

While Salience theory provide some insight into participants' attitude, other areas require investigating perhaps using a combination of theories; for instance salience with regret or disappointment. Since additional data is required to permit statistically reliable conclusions, the suggestions hereof is for future research.

8.4 Avoidance/Seeking of payoffs in the Neighbourhood of Zero

The discussion here builds on the principles driving zero avoidance (seeking) in the case of discrete prospect that when a DM is 'guaranteed' a non-zero strictly positive (negative) payoff compared to an alternative prospect with a downside (upside) having the possibility of zero payoff; a zero averse DM will avoid (choose) the alternative prospect. This suggest that in the gain domain for instance, the reason that drives the decision of a zero-averse (seeking) DM is the dislike for zero payoff rather than the attraction of the non-zero outcomes. However, in the case of continuous prospects employed in this study, this dislike or attraction is not zero avoidance/liking but avoidance/seeking of the area in the neighbourhood of zero.

To investigate possible existence of avoidance of the area in the neighbourhood of zero, first a piecewise power utility function was set up with a kink in the middle obtained from inserting a steep linear component around some narrow region around zero as shown in blue line representing the piecewise power in Figure 38.

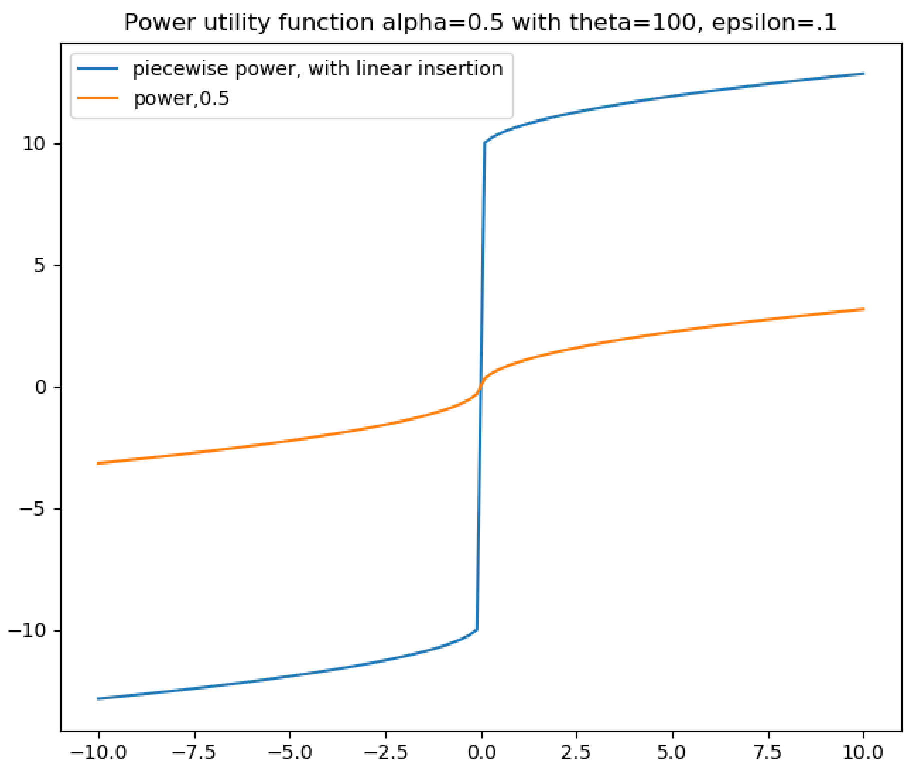


Figure 38. Power utility function

The effect of avoidance of the area in the neighbourhood of zero on certainty equivalents for the discrete case estimation relied on payoffs of 50/50 prospects with two payoffs wherein the upper bound is 50 and the lower bound decreasing progressively towards zero. A plot of the data is presented in Figure 39. The CE plot of this hypothetical data does not show 'abnormal' behaviour in regions close to zero.

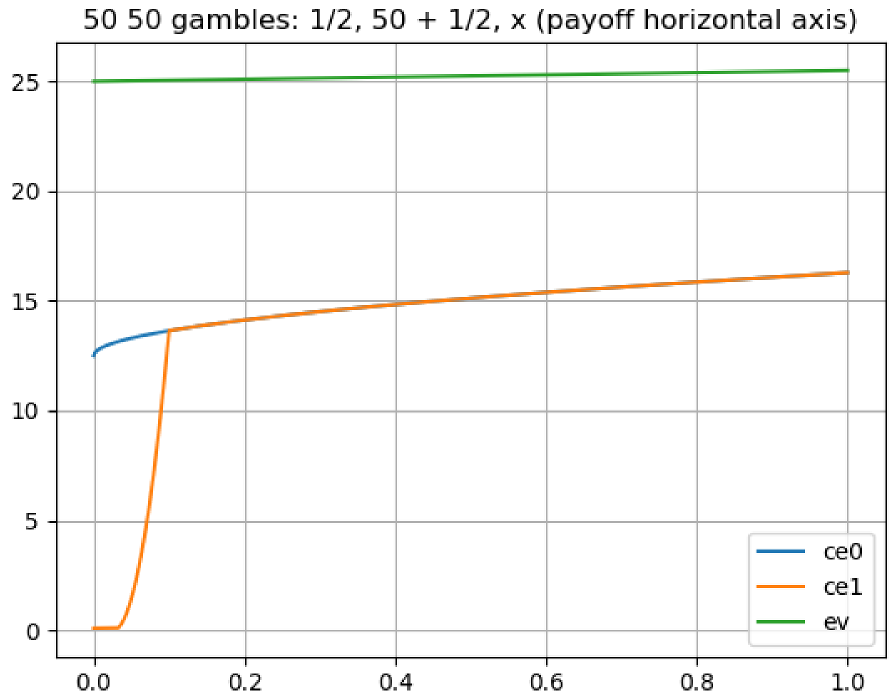


Figure 39. EV and CE of 50-50 lottery

Further, presented in Figure 40 is the continuous equivalent of Figure 39 showing a combination of extreme probability weightings (the beta weighting scheme is employed in this case) that permits quite 'extreme' zero avoidance whereby DMs are not actually avoiding zero but regions in the neighbourhood of zero. However, plotting the CE of uniform prospect and beta weightings show that; where the regions do have neighbourhoods close to zero (suggested by the green line in Figure 40) the attitude of the DM does not suggest extreme risk aversion that was reported for participants' in the Bayesian mixed logit in Chapter 7.

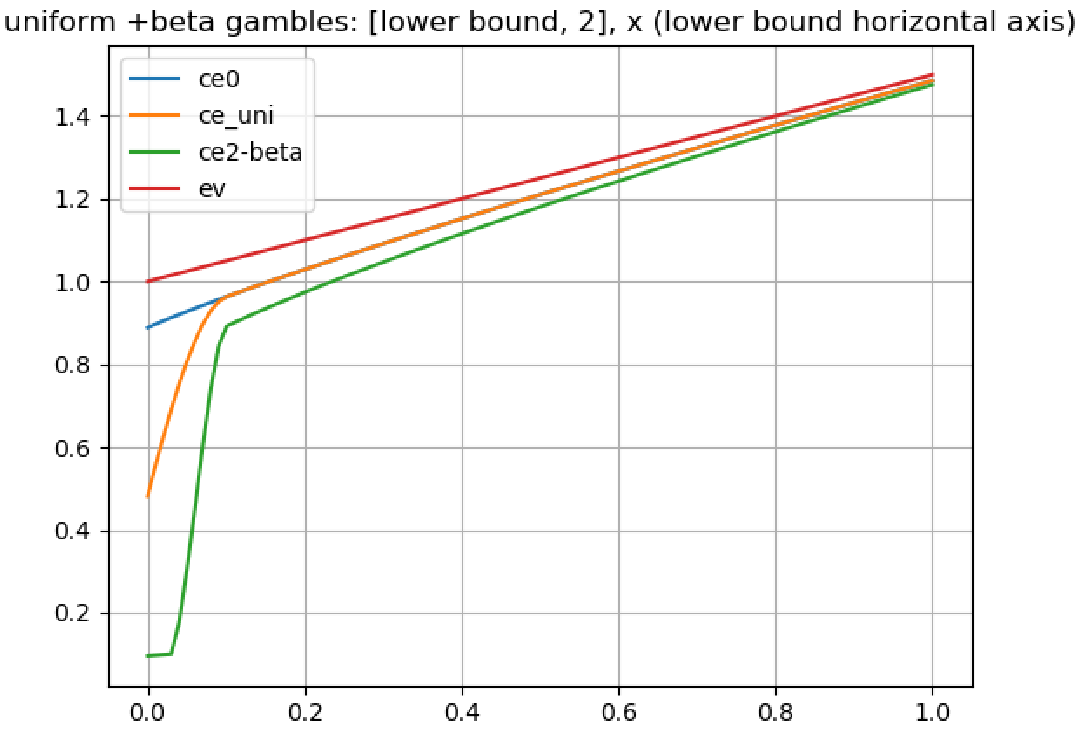


Figure 40. EV and CE of uniform prospect and beta weighting

In line with arguments of the few studies that have reported zero avoidance (*e.g.* Payne (2005), Ert & Erev (2010), Cettolin & Tausch (2015)); one possible explanation for the difference in risk and uncertainty attitude between strict gains for instance and zero-bound gains could be dependent on participants' unwillingness to take chances which may result in not getting a strict positive payoff. In the real world, the economic situation of the participants' may have skewed their preferences by influencing their perception of zero payoffs notwithstanding its possibility of occurring is zero. Thus, zero may have been treated as a 'loss' in the gain domain and vice-versa suggesting that a guarantee of winning something or not losing anything at the very least may be the main aspiration for DMs. The implication of this behaviour is participants' may choose prospects that increases (reduces) the likelihood of a strict gain (loss) even at the expense of lower expected value.

It is not within the scope of this thesis to attempt a full implementation of this model as an extension of the mixed logit model earlier presented. However, future work may investigate this as a possible extension.

8.5 Summary

This chapter focuses on exploring decision rules and alternative theories with the aim of shedding light on the finding in Chapters 6 and 7 relating to significantly large number of non-switching at different points in risk preference ladder, bunching of individuals at the end of the parameter space and '*negligible gain avoidance'* ('*negligible loss seeking'*) in the gain (loss) domain.

In summary, although we find that zero outcomes may have generated certain 'biases', the decision taken by participants in accordance with their choices was not muddled by misunderstanding as participants' showed they understood the experiment. Also, certain proportion of the sample choices conforms to maximin and minimax predictions. However, it was not statistically sufficient to conclude that the maximin and minimax heuristic predicts the predominant choices overall.

As for salience theory, it failed to justify the findings of '*negligible gain avoidance'* and '*negligible loss seeking'.* This limitation could stem from the fact that it is primarily designed for discrete lotteries that are state contingent. However, the prospect used in this study are continuous and do not fit states settings. Although this does not rule out the possibility that DMs implicitly imputed or assumed state dependence before making comparison. Also, DMs may have inferred covariance between outcomes implying a joint distribution rather than marginal distribution. These presumptions need detailed investigation in future studies.

The avoidance of the area in the neighbourhood of zero is used to explain the '*negligible gain avoidance'* and '*negligible loss seeking'* by employing a combination of extreme probability weightings that allows the presence of quite "extreme" avoidance in the neighbourhood of zero. The results show that when the regions do have neighbourhoods close to zero the behaviour of the DM becomes "normal".

Crucially, this Chapter finds that no single heuristics or theories single-handedly justifies all the observed behaviours of participants. However, each theory contributed to explaining certain behaviour of participants thus indicating that typologies of individuals may have adopted different decision rules that may well reflect those that are used in their day-to-day decision making even if it may not be rational.

Chapter 9

Risk and Uncertainty Attitudes - Implications for Farm Decision Making

9.0 Introduction

This chapter utilizes the estimated parameter values under risk and uncertainty attitudes obtained in Chapter 7 to ascertain the relationship between farmers' risk and uncertainty attitudes and bipolar disorder tendencies and; risk/uncertainty attitudes and decision to participate in off-farm income earning activities.

As detailed in Chapter 4, the probit equation presented in equation *4.5.9* is estimated in other to determine the relationship between risk attitude and decision to engage in off-farm income generating activities. To determine factors that influences preference for the type of off-farm income generating activities (OFIGA), the multinomial probit presented in equation *4.6.13* is estimated while the effect of bipolar tendencies on risk attitude is determined from estimating a multivariate multiple regression.

This chapter consist of three sections as follows. In section 9.1 the relationship between risk/uncertainty attitudes and bipolar propensities is reported. In section 9.2 the results of empirical test of relationship between risk/uncertainty attitudes and off-farm participation decisions are presented; followed by determinants of the type of off-farm income generating activities chosen by farmers in section 9.3.

9.1 Risk and Uncertainty Attitudes and Bipolar Disorder Tendencies

This section reports the results of the effect of bipolar disorder tendencies on risk/uncertainty attitudes. In order to test the hypothesis that BD affects risk/uncertainty attitude, this study draws from the psychological concept of outcome sensitivity suggesting that *a priori*, farmers with BD tendencies are more sensitive to changes in outcome as they move further from the reference point. In addition, it is expected *a priori* that that BD tendencies also affect the elevation and slope of the probability weighting function such that farmers with BD tendencies[60] will be more optimistic (pessimistic) for gains (losses).

As discussed in Chapter 2, bipolar disorder tendencies and farmers' mood during the duration of the experiment are the key variables in the regression model. Recall in Chapter 7 the interpretation accorded the CPT parameters that the curvature of the value function that describes the risk/uncertainty attitude is determined by α and β for the domains of gains and losses respectively. The parameter λ on the other hand symbolizes differences in the weight attached to loss compared to gain. As for the elevation captured by δ, higher values represent more optimism in the gain domain. While for the curvature of the probability weighting function determined by γ captures the strength of the deviation of the probability weighting function from linear.

Two models were estimated with the key dependent variables being bipolar tendencies and mood. Bipolar tendencies (Bipolar) describes the effect of borderline to severe bipolar tendencies on risk and uncertainty. Mood captured the state of mind/feeling prior to the risk and uncertainty experiment. In addition to the main variables of interest, other control variables included in the estimated models are age and gender. Model I estimated the effect of Bipolar, mood and *Bipolar*Mood* on all the 8 CPT parameters (α, β, λ, γ^{+}, γ^{-}, δ^{+}, δ^{-}, φ) under risk while model II estimated the same parameters but under uncertainty.

[60] Bipolar disorder as discussed in Chapter 2 is characterised by episodes of both elevated and depressed mood thus the above expectation is referring to a case when the participant is in a good mood.

The results discussed hereafter are from the regression examining the effect of bipolar disorder tendencies on risk attitude only (since bipolar disorder tendencies has no significant effect on most uncertainty attitude parameters. The estimated model has a Roy's largest root of 4.30 (for model II 2.04) with a p-value below 0.01(*resp*. 0.05), suggesting therefore that there are significant differences in the group means for the combination of regressors.

As presented in Table 16, the variable 'bipolar tendencies' is significant and has a positive effect on the shape of the subjective value function for losses (β). This result implies that farmers' with bipolar disorder tendencies show greater risk aversion for losses. The implication of this finding is that characterizing DMs having bipolar tendency by a generalized propensity to take risk without reference to domains and mood/state of mind when the decision is taken may be misleading. This finding corroborates Chandler *et al.,* (2009) findings that compared to healthy controls; the choices of participants BD were less risk seeking when presented with loss framed gambles.

Bipolar tendencies is significant and has a positive relationship with the elevation of the probability weighting function in both the gain and loss domains (*i.e.* δ^+ and δ^-) which translates to farmers with bipolar disorder tendencies are more likely to be more optimistic for gains and pessimistic for losses. This behaviour differ from the results in Chapter 7 that show the average farmer is pessimistic for gains and optimistic for losses. This behaviour could be justified from the point that in certain states of BD, there is very low threshold of describing gains which resulting in excessively optimistic attitudes.

In addition, bipolar tendencies is significant and has a positive relationship with the curvature of the PWF for gains γ^+; suggesting that the probability weighting function of farmers' having bipolar propensities is closer to being linear compared to farmers' that do not show bipolar propensities. Bipolar tendencies also has a significant and negative relationship with choice sensitivity φ suggesting that farmers that have bipolar propensities are more likely to make random choices compared to those without. This finding suggest that BD affect attitudes and may impede optimal decision which can have negative consequences.

Table 16

Multivariate Regression Examining the effect of Bipolar Disorder Tendencies on Risk Attitude

		Risk		Uncertainty	
Dependent Variable	Independent Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
α	Bipolar	0.787	0.527	0.299	0.527
	Mood	0.211	0.327	0.197	0.327
	Bipolar*Mood	-0.539	0.571	-0.016	0.571
	Age	0.172***	0.058	0.071	0.058
	Gender	0.008	0.126	0.233**	0.126
β	Bipolar	1.380***	0.490	0.441	0.599
	Mood	0.442	0.303	0.500	0.371
	Bipolar*Mood	-1.192***	0.531	-0.359	0.649
	Age	0.061	0.054	-0.087	0.066
	Gender	0.042	0.117	0.175	0.143
λ	Bipolar	0.816	0.713	0.185	0.485
	Mood	0.223	0.442	0.104***	0.300
	Bipolar*Mood	-0.854	0.773	-0.020	0.525
	Age	-0.084	0.078	0.110	0.053
	Gender	0.144	0.171	0.127	0.116
γ^{+}	Bipolar	0.743*	0.423	0.189	0.546
	Mood	0.255	0.262	0.439	0.339
	Bipolar*Mood	-0.479	0.458	-0.256	0.592
	Age	0.140***	0.046	-0.125	0.060
	Gender	0.007	0.101	0.083	0.131
γ^{-}	Bipolar	0.562	0.387	0.009	0.231
	Mood	0.243	0.240	0.152	0.143
	Bipolar*Mood	-0.481	0.419	0.044	0.250
	Age	-0.023	0.042	0.010**	0.025
	Gender	-0.008	0.093	0.045	0.055
δ^{+}	Bipolar	0.792**	0.376	0.703	0.500
	Mood	0.307	0.233	-0.003	0.310
	Bipolar*Mood	-0.590	0.408	-0.723	0.542
	Age	0.076*	0.041	0.035**	0.055
	Gender	0.060	0.090	-0.014	0.120
δ^{-}	Bipolar	0.863*	0.481	-0.769	0.644
	Mood	0.496*	0.298	0.063	0.399
	Bipolar*Mood	-0.762	0.521	0.786	0.697
	Age	0.102*	0.053	-0.050	0.071
	Gender	-0.065	0.115	0.040	0.154
φ	Bipolar	-21.288**	12.178	0.372	10.149
	Mood	-8.093	7.545	-1.445	6.287
	Bipolar*Mood	16.790	13.195	-1.928	10.996
	Age	-1.169	1.336	-1.034	1.113
	Gender	0.586	2.914	-3.074	2.429

****** p<0.01, ** p<0.05 and * p<0.1.*

Hypothesis 6: DMs having bipolar disorder tendencies have significantly different risk and uncertainty attitude from DMs with no bipolar disorder.

In other to test the above hypothesis, a Welch's t-test [61] was used to compare the average risk and uncertainty attitude of both groups. The result show statistically significant mean difference between the risk attitude of farmers having bipolar disorder tendencies and those without at the 10% level ($t = -1.79$, $p < 0.092$) in the gains domains only. Therefore, the null hypothesis is rejected and the conclude that the hypothesis that farmers having bipolar disorder tendencies have significantly different risk attitude from farmers with no bipolar disorder is true at 95% confidence level.

Mood is positive and significant for the elevation parameter δ^{-} suggesting that farmers in good mood attach substantially higher weights to probabilities associated with losses. Thus, they show more pessimism for losses compared to farmers in bad mood. This finding conforms with that of Kliger & Kudryavtsev, (2014), Arkes, Herren & Isen, (1988) and Isen, & Geva, (1987) and possibly supports the position of the *mood-maintenance* hypothesis that suggest DMs tend to be risk averse when in a positive mood so as not to interfere with their current state. In other words, DMs become reluctant to take risks particularly if the possible outcomes bring about losses that consequently switch the state of good to bad mood.

Since bipolar disorder is characterised by episodes of depression and mania, the interaction between bipolar tendencies and mood test the hypothesis that there is difference in the effect between bipolar disorder and risk parameters in good mood compared to the bad mood. The negatively significant *mood x bipolar* coefficient suggests that bipolar tendencies and mood interact in influencing risk attitude. This means that the effect of bipolar disorder is smaller among farmers that are in good mood compared to those in bad mood.

Age has a significant and positive relationship with curvature of the value function in the gains domain α, indicating that additional years to the age of the farmers result

[61] The Welch (1947) t-test is chosen based on its reliability in cases where unequal sample sizes and variances occur.

in increased risk seeking for gains. In addition, the coefficient of δ^+ and δ^- further suggest that age increases optimism for gains and decreases pessimism for losses.

The key findings of the above results is that risk and uncertainty attitudes are temporally variable and influenced by the mental health of the DM, which in turn influences decision-making behaviour. Specifically, DMs' mood determines the weights attached to probabilities and bipolar disorder tendencies influences the formation (curvature and elevation) of the probability weighting function. Crucially, individuals with BD tendencies are more likely to make random choices. The implication of this is that a DMs' reasoning and behaviour may be distorted which may result in behaviour that is less 'rational' and perhaps unrealistic.

9.2 Risk/Uncertainty Attitudes and Decision to Participate in Off-farm Income Earning Activities

Recall that the Probit model presented in Chapter 4 estimates the effect of risk and uncertainty attitudes on off-farm income earning activities (OFIGA) participation. The results obtained from the Probit regression are presented in Table 16. Five (5) models were estimated to determine the effect of 'selected variables' on OFIGA participation. This selection was guided by the relationships identified from previous studies in the literature and discussed in section 2.5 in Chapter 2.

Model I estimated the effect of bipolar tendencies alone on OFIGA participation, Model II estimated the effect of risk attitudes (using parameters obtained from the CPT in Chapter 7) on OFIGA participation while Model III incorporates bipolar tendencies, risk attitudes and socioeconomic characteristics in the estimation. Models IV and V are similar to Model III and IV respectively but for uncertainty. Wald test confirm that the variables included in all five models are not simultaneously equal to zero at the 5% level (Model I: χ^2 (1) =3.85, p = 0.04, Model II: χ^2 (6) =29.94, p < 0.001, Model III: χ^2 (21) =78.51, p < 0.001, Model IV: χ^2 (6) =15.03, p = 0.02, Model V: χ^2 (21) =66.71, p < .0001). Models III and V had the highest chi square values. These significant chi square values suggest that the inclusion of these variables enhances the model and results in a better fit. Models III and IV is chosen for discussion hereafter based on goodness of fit criteria including the AIC, pseudo R^2, likelihood ratio (lr) test and Wald test.

The results for the models incorporating risk and uncertainty parameters are similar. Therefore, the discussion in this section will be concurrent with any major differences highlighted. Whether or not farmers engaged in OFIGA was *a-priori* expected to be explained by risk and uncertainty parameters and bipolar tendencies while controlling for age, gender, marital status, education, farm size, farm ownership, geographic location and time spent on the farm.

As presented in Table 17, bipolar disorder has a significant negative relationship with OFIGA participation. This implies that a change from no-bipolar to bipolar tendencies decreases the probability of participating in OFIGA by about 28% suggesting that farmers' having bipolar disorder tendencies are less likely to participate in OFIGA. One explanation for this could be adduced from the discussion Section 2.4 in Chapter 2 regarding the challenge mental health related factors has on job performance and the resultant difficulty people with BD have at their place of work thereby they may be less inclined to participate in OFIGA.

β is positive and significant suggesting that farmers that are more risk averse in the loss domain are more likely to participate in OFIGA. In other words, a one-unit increase in the β increases the probability of participating in OFIGA by 17%. This is rational, as farmers who engage in OFIGA may have done so to complement farm income with OFIGA that may have much lower income 'uncertainties' and possibly lower chances of monetary losses. Hence, this findings can possibly explain the view point of Canning (1992) and Bardhan *et al.,* (2006) that OFIGA participation is mostly a risk management tool that 'pulls' risk averse farmers (particularly for monetary gains) to participate in; with the objective of "cushioning" uncertainties associated with farm income.

δ^- is negative and significantly affects OFIGA suggesting that a unit increase in δ^- (that being less pessimistic) will decreases the probability of participating in OFIGA by about 15% holding other independent variables constant. In contrast with the findings regarding β, this result show that the manner in which farmers use probabilities may not reflect their risk preferences in its entirety since a risk averse farmer may be optimistic in terms of probability weightings.

As for the control variables, age has a significant negative relationship with OFIGA participation indicating that older farmers are less likely to partake in OFIGA compared to younger farmers. A year increase in age decreases the probability of participating in OFIGA by 1%. This is justifiable as it is common in the study area for younger farmers to have the physical capabilities to work off-farm. Bhatta & Arethun, (2013) and Agwu, Nwankwo & Anyanwu (2014) in different context have reported similar results.

Table 17

Marginal Effect after Probit Regression Estimating the Effect of Risk/Uncertainty Attitudes on Off-farm Participation Decision

	No Risk or Uncertainty		**With Risk Parameters**				**With Uncertainty Parameters**			
	Model I		**Model II**		**Model III**		**Model IV**		**Model V**	
Variables	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**
Bipolar	-0.223**	0.109			-0.285***	0.078			-0.279***	0.079
α			-0.191**	0.094	0.075	0.080	-0.030	0.082	0.115	0.076
β			-0.021	0.077	0.117**	0.067	-0.353**	0.139	-0.150	0.124
γ^{+}			-0.009	0.112	-0.118	0.080	0.100	0.093	-0.079	0.092
γ^{-}			0.195**	0.089	-0.072	0.072	0.470**	0.165	0.146	0.144
δ^{+}			0.169	0.131	-0.066	0.103	-0.044	0.148	-0.126	0.156
δ^{-}			0.014	0.071	-0.156**	0.064	-0.035	0.051	-0.142**	0.072
Age					-0.010***	0.003			-0.009***	0.003
Gender					-0.076	0.061			-0.053	0.061
MStatus					-0.120	0.124			-0.251*	0.129
PriEdu					-0.072	0.073			-0.066	0.073
SecEdu					0.129	0.089			0.111	0.091
HigherEdu					-0.100	0.103			-0.127	0.124
HHsize					0.001	0.013			0.001	0.014
Farm Type					-0.448***	0.161			-0.507***	0.169
Farm Tenure					0.267**	0.117			0.217*	0.125
Farmhours					-0.030	0.019			-0.033	0.023
Farmsize					-0.204***	0.052			-0.206***	0.051
Location					0.113**	0.054			0.177***	0.060
Cooperative					-0.147**	0.073			-0.122	0.077
Rural					-0.340***	0.092			-0.120*	0.065

Note. Dependent variable = Participation in off-farm income generating activities (OFIGA) where OFIGA= *1 if Farmer engages in off-farm income generating activities, 0 otherwise* *** p<0.01, ** p<0.05 and * p<0.1.

Against *a-prior* expectation, education had no significant effect on the probability of being involved in OFIGA. This finding may be attributed to the significantly large proportion of the sample (65%) having either no formal or completing primary education at the most. Typically, in Nigeria smallholder farming is considered a 'residual' occupation that accommodates mostly those with little or no capacity to seek other non-farm alternatives. This result is in consonance with Beyene (2008) who reports that household participation in off-farm activities is not influenced by level of education. However, it contradicts Babatunde, (2013) and McCarthy & Sun, (2009) findings that individuals with higher level of education tend to allocate more time to off-farm income generating activities.

Marital status has a significant negative effect on OFIGA participation though for uncertainty only. A change from single to married decreases the probability of participating in OFIGA by 25%. This indicates that married farmers are less likely to engage in OFIGA that their single counterparts. This finding is similar to De Brauw & Rozelle, (2008).

Farm type is negative and significant for OFIGA participation indicating that farmers operating monoculture[62] have a lower likelihood of engaging in OFIGA. This suggest that a change in farm type decreases the probability of participating in OFIGA by 44%. This inverse relationship could be attributed to risk/uncertainty attitude as farmers who practice monoculture may be more risk seeking (for gains) hence invest all their resourses in one crop or animal despite the risk of losing everything.

Farm size is negative and significant for OFIGA participation indicating that farmers cultivating larger farm have a lower likelihood of engaging in OFIGA. A one-unit increase in farm size decreases the probability of participating in OFIGA by 20%. This inverse relationship may be related to wealth levels associated with farm size and a reflection that land constraints possibly encourages off-farm participation. This result supports Alasia *et al.,* (2009) and Fernandez-Cornejo *et al.,* (2007) separate findings of inverse relationship between income from off-farm and farm size.

[62] Monoculture is an agricultural practice whereby a farmer grows only one crop type or raises a single species of animal. The alternative to monoculture is polyculture.

In addition, there is significant positive relationship between farm tenure and OFIGA participation indicating that farmers who own their land are more likely to participate in OFIGA than those who rented land. While this is Contrary to VanWey & Vithayathil (2013) and may appear counter intuitive at first instance, however farmers that operate on rented or leased land have additional burden of paying rent out of their farm returns compared to their counterpart that own land. This may induce renters to work the land more compared to landowners so that they can get maximum benefit from their investment. Finally, farmers in rural areas are less likely to participate in OFIGA. A change from urban to rural decreases the probability of participating in OFIGA by 34%. This could be justified from the perspective that compared to urban dwellers there may be less off-farm income generating activities available to rural dweller.

9.3 Determinants of Preference for the Types of Off-farm Income Generating Activities

In line with the discussion in Chapter 4, for the multinomial probit regression (MPR hereafter) the comparison is between the baseline "No OFIGA" and the three OFIGA categories *i.e.* employee, worker and self-employed. The results of the marginal effect after multinomial probit regression examining the determinants of the choice of OFIGA are presented in Table 18.

Similar to section 9.2, five (5) models estimated the effect of selected variables on the types of OFIGA engaged in by farmers. Model I estimated the effect of bipolar tendencies alone on types of OFIGA, Model II estimated the effect of risk attitudes on types of OFIGA engaged in while Model III incorporates bipolar tendencies, risk attitudes and socioeconomic characteristics in the estimation. Models IV and V are similar to Model III and IV respectively but for uncertainty. A confirmation that the models are not simultaneously equal to zero was obtained from the Wald test at the 5% level (Model I: χ^2 (3) =5.64, p = 0.14 NS, Model II: χ^2 (18) =30.19, p =0.03, Model III: χ^2 (63) =169.30, p < 0.001, Model IV: χ^2 (18) =39.54, p = 0.002, Model V: χ^2 (63) =177.03, p < .0001). Thus, the inclusion of these variables enhances the model and results in a better fit. Given the results for the risk and uncertainty models are similar, subsequent discussion in this section will refer to both models concurrently. Models III and IV are the most preferred models based on the criteria of the AIC, pseudo R^2, likelihood ratio (lr) test and Wald test.

Table 18 *Marginal Effect after Multinomial Probit Examining the Determinants of the Type of OFIGA*

	No Risk or Uncertainty		**With Risk Parameters**				**With Uncertainty Parameters**			
Variables	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**
1 = Employee										
Bipolar	-0.212	0.153			-0.262	0.166			-0.282*	0.148
α			-0.005	0.102	-0.038**	0.134	0.085	0.105	0.231*	0.140
β			0.172*	0.073	0.189	0.092	0.085	0.112	0.244*	0.134
γ^+			0.088	0.114	0.095	0.134	-0.008	0.117	-0.171	0.145
γ^-			-0.051	0.090	-0.037	0.108	0.032	0.135	-0.169	0.158
δ^+			-0.192	0.126	-0.163	0.175	-0.612***	0.206	-0.766***	0.267
δ^-			-0.079	0.080	-0.043	0.099	-0.248***	0.089	-0.388***	0.114
Age					0.003	0.004			0.005	0.004
Gender					-0.053	0.094			-0.052	0.094
MStatus					0.357	0.226			0.349*	0.208
PriEdu					0.173	0.107			0.156	0.103
SecEdu					0.030	0.134			0.019	0.120
HigherEdu					0.054	0.178			0.029	0.169
HHsize					-0.024	0.019			-0.027	0.019
Farm Type					-0.427**	0.171			-0.363**	0.179
Farm Tenure					0.068	0.127			0.003	0.138
Farmhours					-0.057**	0.029			-0.066**	0.031
Farmsize					-0.111	0.071			-0.101	0.081
Location					0.135	0.083			0.177**	0.087
Cooperative					-0.044	0.127			-0.105	0.117
Rural					-0.090	0.123			-0.124	0.093

N = 158, Reference = *Farmer not participating in any off-farm job.*
**** p<0.01, ** p<0.05 and * p<0.1.*

	No Risk or Uncertainty		With Risk Parameters				With Uncertainty Parameters			
Variables	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
2 = Worker										
Bipolar	-0.132	0.109			-0.118	0.184			-0.103***	0.175
α			-0.166	0.114	-0.189	0.139	-0.330***	0.108	-0.442	0.130
β			-0.122	0.086	-0.111	0.105	-0.114	0.126	-0.123***	0.150
γ^{+}			-0.102	0.127	-0.105	0.152	0.346***	0.122	0.420	0.135
γ^{-}			0.102	0.099	0.063	0.13	0.255*	0.149	0.263	0.179
δ^{+}			0.236*	0.139	0.227	0.174	-0.034	0.208	0.104	0.242
δ^{-}			0.070	0.079	0.040	0.104	0.114	0.099	0.215*	0.120
Age					-0.002	0.005			-0.005	0.004
Gender					-0.011	0.094			0.024	0.102
MStatus					-0.310*	0.168			-0.381**	0.164
PriEdu					0.051	0.113			0.039	0.118
SecEdu					0.283**	0.140			0.325**	0.134
HigherEdu					-0.121	0.197			0.006	0.191
HHsize					0.004	0.020			0.010	0.021
Farm Type					0.026	0.216			-0.128	0.211
Farm Tenure					-0.126	0.173			0.055	0.183
Farmhours					-0.033	0.034			-0.020	0.035
Farmsize					-0.147*	0.088			-0.174*	0.090
Location					0.042	0.087			0.028	0.094
Cooperative					0.202	0.148			0.211	0.139
Rural					-0.075	0.166			-0.059	0.109

N = 158, Reference = *Farmer not participating in any off-farm job.*
**** p<0.01, ** p<0.05 and * p<0.1.*

	No Risk or Uncertainty		With Risk Parameters				With Uncertainty Parameters			
Variables	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**	**dy/dx**	**Std. Err.**
3 = Self-employed										
Bipolar	0.094	0.121			0.000	0.128			0.011	0.134
α			0.117	0.100	0.305***	0.117	0.317**	0.124	0.388***	0.122
β			-0.053	0.083	0.056	0.095	-0.158	0.110	-0.234*	0.131
γ^{+}			-0.034	0.102	-0.135	0.117	-0.377***	0.139	-0.419***	0.137
γ^{-}			0.057	0.094	-0.108	0.116	-0.024	0.131	0.004	0.158
δ^{+}			-0.125	0.116	-0.138	0.143	0.426**	0.208	0.524*	0.225
δ^{-}			-0.127*	0.071	-0.196**	0.087	-0.022	0.099	-0.009	0.119
Age					-0.015***	0.004			-0.013***	0.004
Gender					-0.023	0.096			-0.015	0.099
MStatus					-0.223	0.156			-0.299*	0.160
PriEdu					-0.314***	0.105			-0.273***	0.103
SecEdu					-0.154	0.116			-0.191*	0.109
HigherEdu					-0.039	0.156			-0.159	0.172
HHsize					0.023	0.020			0.022	0.019
Farm Type					-0.221	0.158			-0.175	0.183
Farm Tenure					0.463***	0.160			0.278	0.171
Farmhours					0.055**	0.030			0.045	0.030
Farmsize					-0.005	0.078			0.018	0.082
Location					-0.019	0.078			0.030	0.077
Cooperative					-0.367***	0.132			-0.276*	0.143
Rural					-0.285**	0.120			0.005	0.094

N = 158, Reference = *Farmer not participating in any off-farm job.*
**** p<0.01, ** p<0.05 and * p<0.1.*

9.3.1 *Employee* relative to No-OFIGA

As presented in Table 18, bipolar disorder has a significant negative relationship with the type of OFIGA participation. This implies that a change from no-bipolar to bipolar tendencies decreases the probability of taking up fixed regular paid employment by about 28% suggesting that farmers' having bipolar disorder tendencies are less likely to engage in regular paid employment compared to relying on income derived solely from farming. In line with the reasons adduced earlier in Section 9.2, the challenge mental health related factors has on job performance and the resultant difficulty people with BD have at their place of work could be responsible for this effect.

The significant negative value of α indicates that the relative probability of taking up fixed regular paid employment[63] compared to engaging solely in farming reduces by 3% as farmers becomes less risk averse by one unit. That is, the chances of choosing to take up a regular paid employment are lower amongst farmers that are more risk seeking for gains. This is rational as it is expected to find more risk averse farmers participating in this category of OFIGA since risk averse farmers will prefer the 'assured' but possibly lower earnings from paid employment than to 'gamble' at earning more (*albeit* with possibility of earning less or nothing) by relying solely on farming. Thus, farmers taking up fixed regular paid employment as an off-farm activity may do so for the reason of providing a buffer against anticipated farm risk and as a "*necessity*" rather than taking advantage of an "*opportunity*" to make additional income as characterised by their risk seeking counterpart.

The result is however different for attitudes to uncertainty given that the probability of taking up fixed regular paid employment compared to engaging solely in farming increases by 23% with a unit increase in α. This suggest that the likelihood of choosing to take up a regular paid job is higher amongst farmers that are more uncertainty seeking for gains. This finding does not conform to *a-priori* expectation as the greater tendency would have been to observe farmers that are uncertainty

[63] Jobs captured in the employee category were mainly off-farm fixed regular (weekly or monthly) wage employment including teaching, shop keeping, security guards *etc*.

averse for gains having greater tendency to participating in all categories of OFIGA. A possible explanation could be that DMs become uncertainty seeking (possibly due to 'overconfidence'). Such overconfidence may arise from the propensity to set excessively optimistic prediction of uncertain events in the case where the probability density of outcomes are not clearly defined.

The significant positive value of β suggest that a unit increase in β will increase the chances of engaging in fixed regular paid employment by 24%. In other words, farmers that are less risk seeking for losses under uncertainty are more likely to engage in fixed regular paid employment. This could be justified from the perspective that since the farm prospect has likelihood of loss in farm income, thus farmers that are averse to uncertainty will prefer the 'assured' earnings from OFIGA to complement farm income rather than rely solely on the farm earnings.

As for the socioeconomic variables; marital status and location have positive effect on the type of OFIGA while farm tenure and time spent farming have negative effects on the type of OFIGA.

9.2.2 *Worker* relative to No-OFIGA

Bipolar disorder has a significant negative relationship with the type of OFIGA participation. This implies that a change from no-bipolar to bipolar tendencies decreases the probability of taking up causal wage employment by about 10% suggesting that farmers' having bipolar disorder tendencies are less likely to engage in causal wage employment compared to relying on income derived solely from farming. Again, the reasons adduced earlier regarding mental health related factors, employment difficulty and job performance could be responsible for this effect.

As presented in Table 18, the variable β is negative and significant for worker[64] indicating that relative probability of taking up causal work compared to not participating in any OFIGA decreases by 12%, as uncertainty aversion in the case of losses increases by one unit. In other words, being uncertainty averse for losses decreases the probability of choosing to work off-farm in the worker category.

[64] OFIGA classified as worker refers to causal wage employment such as labourer, temporary factor workers *etc*.

Similar to the case of employee, this finding could be justified from the perspective that when the farm prospect has possibility of loss in farm income, farmers that are averse to uncertainty may prefer the 'assured' earnings from OFIGA.

Regarding the controls, married farmers are less likely fall in the worker category; secondary education is significant and positive suggesting that the relative probability of working off-farm in the worker category against having no OFIGA is higher for farmers that have secondary education compared to those without any formal education. The size of the farm is significant and negatively related to farmers in the worker category indicating that probability of taking up paid employment reduces as farm size increases.

9.2.3 *Self-employed* relative to No-OFIGA

As presented in Table 18, the risk attitude variables α is significant with a positive value indicating that the relative probability of being self-employed[65] compared to engaging solely in farming increases for farmers that are risk and uncertainty seeking for gains. That is, the relative probability of starting one's own business alongside farming compared to not participating in any OFIGA increases by 30% (38%) when risk (uncertainty) aversion for monetary gains decreases by one unit. One explanation for this could be that not all farmers necessarily engage in OFIGA as a cushion for risk as often reported in the literature but rather may be driven by "opportunities" to make supplementary income not withstanding having to face additional uncertainties and risks.

In addition, β and δ^{-} are significant negative determinants of the type of OFIGA under uncertainty as presented in Table 18. This suggest that the relative probability of becoming self-employed alongside farming compared to engaging solely in farming decreases as uncertainty aversion and pessimism for losses increases. In other words, a unit increase in uncertainty aversion and pessimism for losses will decrease the chances of becoming self-employed by 23% and 19% respectively. This could be justified from the perspective that when off-farm prospects have possibilities of resulting in income losses, farmers that are averse to

[65] OFIGA classified as self-employed includes jobs such as food processors, hairdressing, transporting, tailoring, cobbling *etc.*

uncertainty will be less willing to exploit off-farm “opportunities” to make supplementary income from self-employment specifically as the success of starting and sustaining a business involves a lot of decision making under uncertainties. Finally, considering the control variables; age, primary education and membership to cooperatives have negative effect on being self-employed.

9.4 Summary

In summary, this Chapter presents results and discusses the empirical findings of three issues. First, the relationship between risk and uncertainty attitudes and decisions to be involved in off-farm income earning activities was examined. Second, the link between risk and uncertainty attitudes and the nature or type of off-farm activity engaged in was explored. Third, the effect of mental health related factors on attitudes to risk and uncertainty of farmers in the study area is investigated. The probit equation was estimated to determine the relationship between risk attitude and decision to engage in off-farm income generating activities. To determine factors that influences preference for the type of off-farm income generating activities (OFIGA), the multinomial probit presented was estimated while the effect of bipolar tendencies on risk attitude was determined from estimating a multivariate multiple regression.

The main findings in Chapter 9 are; risk and uncertainty attitudes are influenced by mental health of the DM, which in turn influences decision-making behaviour. Specifically, a DMs' mental health determines the weights attached to probability and bipolar disorder tendencies influences the formation (curvature and elevation) of the probability weighting function. Precisely, farmers' with bipolar disorder tendencies show greater risk aversion for losses. In addition, farmers with bipolar disorder are more likely to show higher optimism for gains and pessimism for losses. This behaviour differs from the results in Chapter 7 that show the average farmer is pessimistic for gains and optimistic for losses. Crucially, farmers that have bipolar disorder propensities are more likely to make random choices compared to those without bipolar. Other findings are that the effect of bipolar disorder is smaller among farmers who are in good mood compared to those in bad mood.

Further, the results suggest risk aversion (for losses) increases participation in off-farm income generating activities (OFIGA). Similarly, farmers' likelihood of engaging in specific types of OFIGA (*self-employed, worker* and *employee*) is determined by their risk and uncertainty attitudes as well as mental health related factors.

Chapter 10

Summary, Conclusion and Recommendation

10.1 Summary

Attitudes to risk have generated a lot of attention over the years due to its vital importance in decision-making processes that are necessary for life and livelihoods. Attitudes towards uncertainty have received less attention even though arguably most important decisions are under uncertainty rather than risk. In addition, many studies modelling attitudes to risk have adopted experiments that place significant cognitive burden on respondents. Crucially, they are also framed in a way that do not reflect everyday problems. Specifically, the most common way of eliciting attitudes is to ask people to choose between discrete monetary lotteries with known probabilities attached to the payoffs. Yet, the vast majority of choices that people make in their day-to-day lives are with respect to continuous non-monetary outcomes. As a result, several questions have so far arisen. For instance, are there any methods that best measure risk and uncertainty? Are these measures consistent? Are DMs generally risk averse regardless of domain? Do DMs have the same attitudes *e.g.* to financial *versus* health uncertainties? This study was designed to examine the risk and uncertainty attitude of a farm-household decision maker. Specifically, the sub-objectives were to examine: (*a*) farmers' attitude towards risk in different contexts and content domains; (*b*) farmers' uncertainty attitude in different content domains; (*c*) compare risk and uncertainty attitudes (*d*) examine risk attitude of farmers when taking decision for others (*e*) determine the relationship between bipolar tendencies and risk attitudes; (*f*) examine the relationship between risk attitude and decision to engage in off-farm income generating activities.

This thesis reviewed literature on theories of decision-making, the approaches to eliciting attitudes to risk and uncertainty as well as the role of risk and uncertainty attitude on farmers' decision making with the aim of providing direction to this study. The literature reviewed in this study suggested that theories (including the CPT and CEU) which relies on both the utility function and probability weightings to explain risk attitude does a better job at explaining behaviour compared to those that implicitly assumes expected utility maximisation. Also, predominant elicitation methods in the literature relied mostly on binary lottery choices designs with very limited studies showing interest in extending popular theories to continuous prospects tasks. The review of literature also highlights the fact that risk attitudes in proxy decision in developing countries have not been widely researched. In addition, literature providing empirical evidence on risk and uncertainty attitudes and the relationship between the decision to engage in off-farm income earning activities, the link between risk attitude and type of off-farm activity and the effect of bipolar disorder on farmers' risk attitude was limited.

To achieve the objective of estimating farmers' attitudes to risk and uncertainty in different context and content domains, Bayesian hierarchical CPT model was estimated. The GEE and probit model was used to estimate the determinants of prospect choice. The objectives of examining the relationship between risk and uncertainty attitudes and decision to engage in (as well as the type of) off-farm income generating activities on one hand; and effect of bipolar tendencies on risk attitudes on the other hand were determined from estimating the probit regression and multivariate multiple regression models respectively.

The data used in this study was obtained using two data gathering tools. First, choices under conditions of risks and uncertainties were obtained using an interval '*lottery-style*' experiment that is least as realistic as discrete prospects but more indicative of the kind of choices made by farmers on a day-to-day level. Attitudes towards risk as opposed to uncertainty were elicited by specifying that all outcomes over the specified interval were 'equally likely' (thus specifying a uniform probability density). Uncertainty was communicated by indicating that one outcome within the specified interval would be realised but without the specification of an associated probability density. Second, a two-part questionnaire with the first section capturing socioeconomic characteristics and the second section modified Bipolar Spectrum Diagnostic Scale (originally designed by Ghaemi *et al.,* 2005) was issued to participants. Multistage sampling technique was used to obtain the respondents of the study. The number of participants that took part in the experiment and completed the questionnaire was 158.

By relying on graphs, proportions and non-parametric tests to describe and explain the choices made by participants during the experiment, the results presented suggests that participants' choices in the experiment are heterogeneous. In addition, under conditions of risk or uncertainty; participants find the inner prospect more attractive for gains (and mixed task) and the outer more attractive for losses. Since the inner prospect is by nature less 'risky', this finding indicated participants' dislike for risk and uncertainty in the gain (and mixed) domain; and love for risk and uncertainty in the loss domain. Further hypotheses testing suggest that participants' choices differ across content (gain, loss, mixed) domains. In addition, the results suggest that participants' choices differ with context (*i.e* monetary *vs.* time). Participants prefer the 'risky' prospect more when making choices on money compared to time *i.e.* participants took more 'risk' when making choices on money compared to time. Regarding whether attitudes to risk differ when making decision on behalf of others; the results show that participants prefer less 'risky' prospect more when making choices for themselves compared to the choice on behalf of others *i.e.* participants disliked 'risk' more when making choices for themselves compared to the choice on behalf of others.

The results obtained from Hierarchical Bayesian CPT model estimation suggest that at individual level, risk and uncertainty attitudes are not homogenous across content (gain, loss and mixed) domains. In aggregate, farmers are risk averse for gains and risk seeking for losses under both risk and uncertainty. However, the test of hypothesis suggest significant difference in the distribution of the curvature of the value function under risk compared to uncertainty implying that attitudes differ under both conditions. In addition, there is evidence of probability weighting for gains and losses. This finding of subjective probability warping in the case of equally likely outcomes imply that farmers' did not always regard equally likely outcomes as 'equally likely'. However, there were behaviours that were difficult to reconcile with CPT, as the preferences of many respondents could only be modelled using "extreme curvature" of the value function. This was induced by what is termed *negligible gain avoidance* (*i.e.* avoiding prospects with zero lower bound in the gain domain) or *negligible loss seeking* (*i.e.* preferring prospects with zero upper bound in the loss domain) behaviours.

By exploring decision rules and alternative theories with the aim of shedding light on the phenomenon of *negligible gain avoidance* and *negligible loss seeking* in the gain and loss domains respectively, the findings suggests that is not simply a deficient level of understanding of the experiment that has led the aforementioned behaviour. Typologies of individuals may have adopted different decision rules that may well reflect those used in their day-to-day decision making even if it may not be "rational".

Finally, the estimation of the effect of bipolar tendencies on risk attitude farmers suggest that risk and uncertainty attitudes are influenced by the mental health of the DM, which in turn influences decision-making behaviour. Specifically, a DMs' mood determines the weights attached to probabilities and bipolar disorder tendencies influences the formation (curvature and elevation) of the probability weighting function. Specifically, farmers' with bipolar disorder tendencies show greater risk aversion for losses. In addition, farmers with bipolar disorder are more likely to show higher optimism for gains and pessimism for losses. This behaviour differs from the results in Chapter 7 that show the average farmer is pessimistic for gains and optimistic for losses. Crucially, farmers that have bipolar disorder propensities are more likely to make random choices compared to those without bipolar. Other findings are that the effect of bipolar disorder is smaller among farmers who are in good mood compared to those in bad mood.

Finally, the results from the estimation of the relationship between risk attitude and decision to engage in off-farm income generating activities show that risk aversion for losses increases OFIGA participation. As for the factors that determines preference for the type of off-farm income generating activities (OFIGA), the results indicates that farmers' likelihood to engage in specific types of OFIGA is determined by their risk and uncertainty attitudes and bipolar tendencies decreases the probability of taking up fixed regular paid and causal wage employment.

10.2 Concluding Statement

Measuring farmers' risk and uncertainty attitudes using interval prospect-choice experiment has highlighted the potential to investigate the vast majority of choices people make in their day-to-day lives with respect to both continuous monetary and non-monetary outcomes without placing significant cognitive burden on respondents. Notably, this unique experiment enables this thesis contribute to the literature examining risk and uncertainty attitudes separately; and underscores the nomenclature where risk and uncertainty is being used in a non-standardised way as the results show attitudes differ under different conditions (risk and uncertainty). Despite facing decisions with continuous prospects, DM do not treat equally likely outcomes as 'equally likely' but demonstrate cumulative probability distribution warping consistent with the Cumulative Prospect Theory. However, not all behaviours can be reconciled with CPT, Salience theory, Heuristics and other theories as reported in this thesis thus accentuating earlier speculations regarding the extent to which these theories reflect actual behaviour under risk and uncertainty. Crucially, in evaluating the determinants of risk/uncertainty attitudes it is important not to overlook biological/physiological traits. Integrating aspects of mental health related issues into the broad decision making literature is justified from several perspectives including the implications of making random choices (consistent with DMs that have bipolar disorder) on lives and livelihood.

10.3 Risk and Uncertainty Attitudes and Implications for Policy Design

From the view-point of policy design implications, the assumed stereotypic homogenous 'risk averse' attitudes attributed to farmers' and the assumption that there is no difference between attitudes under risk and uncertainty by the government could be one of the reasons why in many cases the objectives of policies and projects from successive Nigerian governments are not met. In Nigeria where farmers rely on the government for all kinds of support, this speculative stance may result in inappropriate policies and ill-judged farm support. Since the strength of any policy depends on the quality of empirical findings which drives it, studies of this nature which provide valid empirical based information regarding the risk and uncertainty attitudes of farmers in specific contexts is relevant to assist policy makers take informed decisions.

The findings from this thesis that only the mean (average) rather that both mean and variance had significant effect on the prospect chosen by farmers has implications for policy. Broadly, an intervention or policy that may appear as an advancement or development when viewed from the perspective of smaller variance of expected effect (compared to what already exist) may not necessarily be preferred by farmers especially in the case where farmers focus are on the average benefit they expect to derive. Findings of this nature can help policy makers to thoroughly understand and synchronise farmers' expectations with intervention goals.

Crucially, in designing and executing policies; attention should be paid to framing to avoid unconsciously swaying attitudes under conditions of risk or uncertainty. This is important as the manner in which policies and interventions are framed *i.e.* either as a 'welfare gain' or 'hardship reduction' has the possibility of affecting risk and uncertainty attitudes. In addition, any intervention in which the worst-case scenario has the possibility to leave farmers' with zero benefit may not yield the desired goal as the possibility of 'zero benefit' may result in farmers rejecting such intervention.

Regarding differences in farmers' characteristics, the findings from this study brings to attention the need for tailored policy that accommodates socioeconomic and biological/physiological diversity. With respect to the findings that mental health related factors plays a significant role in determining risk and uncertainty attitudes is a pointer that the farming population also includes vulnerable individuals which government in Nigeria should consider providing targeted support when introducing policies or intervention programmes.

10.4 Contribution to Knowledge and Literature

The contributions of this thesis to knowledge and literature is both methodological and outcome related. These are summarised as follows:

1. By expanding discrete to continuous prospects and testing in a different setting, this study shows the applicability of the interval prospect experiment to different contexts. The findings highlights the continuous prospect experiments are as realistic as discrete lotteries, less cognitively demanding than discrete lotteries and more indicative of the kind of choices made by farmers on a day-to-day level.
2. This thesis subjects decision theories and phenomena including CPT, salience theory and heuristics to experiments involving continuous outcome thereby exposing their capabilities and extent to which their intuition corresponds to actual behaviour of DMs' under risk and uncertainty. Eliciting attitudes with respect to continuous outcomes highlights certain behaviours that are difficult to reconcile with these theories. It further shows that DM's in many cases adopt different rules and heuristics that may not be "rational" in certain context but are crucial in simplifying day-to-day decisions.
3. The findings of probability warping by respondents in this study bring to the fore further evidence that DMs' do not handle 'equally likely' outcomes as though all events of a sample space have the same likelihood of occurring. This finding draws attention to the function of subjective weighting in decision-making and challenges the conclusion of studies that assume that probability weighting can be overlooked for continuous prospects. Thus, it disputes any interpretation that arise from such assumption.
4. Another key finding of this thesis is that attitudes differ under different conditions (risk *vs*. uncertainty), contexts (monetary & time) and domains (gain, loss & mixed). In addition, this thesis is one of few studies that examines risk attitude when a DM is faced with losses in the time context domain; and compares it with attitudes to losses in other contexts.
5. As a contribution to the limited investigation on the possible temporal variability in risk/uncertainty attitudes and the effect physiological traits of a DM has on these attitudes; this thesis amalgamates otherwise independent

ideas of mental health related factors and risk/uncertainty attitudes with the wider implications of understanding how these factors interact and affect decision making.

6. This thesis employs a combination of parameters that measures subjective values of gains/losses and subjective probabilities as a determinant of farmers (off-farm participation) decision-making. From this perspective, it differs from previous studies on two grounds. First, rather than inputting risk and uncertainty attitudes in the estimation model as one single factor affecting decision making as done in previous studies; this study treats risk and uncertainty attitudes as separate variables. Second, the attitudes to risk and uncertainty was obtained by parametric estimation prior to being used as a determinant in the econometric model.
7. This thesis contributes to the broader literature examining risk attitudes in proxy decision in Agricultural Economics (that focuses on farmers in developing countries) which have not been widely researched.
8. Lastly, this thesis contributes to the literature given the dearth of studies addressing the issues above in developing countries where famers risks their livelihoods by being exposed to arguably much larger risks/uncertainties than farmers in developed countries.

10.5 Limitations and Suggestions for future Research

The definition for risk aversion adopted in this thesis restricts the term to describe the value function *albeit* recognises that this does not necessarily correspond to a DM choosing a prospect on the basis of mean preserving spreads. Although this is rationalised from the perspective that the manner in which probabilities are handled by DMs does not actually reflect their risk preferences as such, this definition however have its limitations. To extend the above definition will require that a probability-payoff domain is defined with clear sub-domains over which the DM is risk averse/seeking; however this will lead to further complications and muddling of the nomenclature.

The number of respondents' *(N=158)* although adequate for the objectives of this thesis considering practical limitations; however, findings that are more incisive could be obtained on a larger sample size and the findings generalized to the population. Crucially, increasing the sample size is required where the goal is to link attitudes to risk and uncertainty with farm decisions for the sake of providing empirical evidence to drive future policies.

In designing the experiment, the aim of the thesis was to study several context (monetary and time) and domains (gain, loss and mixed) where participant were presented with 90 pairs of prospect choice task spread across the different context and content domains under risk and uncertainty respectively. This approach had its demerits as the quest to avoid fatigue and cognitive burden became a trade-off with the number of choice tasks presented to each respondents' across each context and domain. Although this does not in any way disparage the outcome from the experiment, future research however could focus on less context and (or) content domains and increase the number of tasks presented to participants.

The finding in this thesis that it matters to participants when the bound of the prospect was pegged at zero but the payoffs still remained strictly positive (or negative) brings to light the possibility of enhancing future visuals presentation the experiment. For instance, by adding cues such as the mid-point to each pair of prospect, excluding from the visual presentation to participants any real numbers that fall within the prospects intervals or adding alongside the continuous prospect a discrete choice problem and possibly introducing more *'zero-bound'* lottery pairs could provide further insight to DMs behaviour. However, these suggestions should be introduced with caution as there are associated shortcomings.

This thesis did not compare different elicitation designs applicable to continuous prospect on participant so cannot conclude that individual heterogeneity is not partly influenced by elicitation method. In future studies, it may be necessary to investigate if individual heterogeneity found among participants is a result of experiment design by comparing different designs on participants in the same study.

Decision-making models including those not identified in this thesis need to be subjected to further rigorous test specifically one that involves continuous prospects to further assess and possibly compare their performances. Although, it has been contended that a CPT model with an extremely steep section provides a framework for the phenomena of *NGA* and *NLS*, however the problem remains that this phenomena has not been widely reported in the context of discrete prospect experiments.

Also, it is not within the scope of this thesis to attempt a full implementation of the model that combine extreme probability weightings to investigate zero avoidance/seeking of payoffs in the neighbourhood of zero as an extension of the mixed logit model used in this study. However, future work may investigate this as a possible extension.

Finally, with respect to developing countries specifically there is prospect for future research to be extended to investigate other types of decision-making such as linking risk and uncertainty attitudes with farmers' adoption, migration, investment or savings decisions. Such finding will have enormous impact on farmers who risks their entire livelihoods by being exposed to arguably much larger risks/uncertainties compared to farmers in developed countries.

References

Abdellaoui, M., & Kemel, E. (2013). Eliciting prospect theory when consequences are measured in time units: "Time is not money". Management Science, 60(7), 1844-1859.

Abdellaoui, M., Bleichrodt, H., & l'Haridon, O. (2008). A tractable method to measure utility and loss aversion under prospect theory. Journal of Risk and uncertainty, 36(3), 245-266.

Abdellaoui, M., Klibanoff, P., & Placido, L. (2015). Experiments on compound risk in relation to simple risk and to ambiguity. Management Science, 61(6), 1306-1322.

Abdellaoui, M., l'Haridon, O., & Zank, H. (2010). Separating curvature and elevation: A parametric probability weighting function. Journal of Risk and Uncertainty, 41(1), 39-65.

Adewumi, M. O., Ayinde, O. E., Olatunji, G. B., & Ajayi, F. F. (2012). Effect of poverty on risk attitude of rural women investors in Osun State, Nigeria.Journal of Agriculture and Social Research (JASR), 12(1), 19-25.

Adomi, E. E., Ogbomo, M. O., & Inoni, O. E. (2003). Gender factor in crop farmers' access to agricultural information in rural areas of Delta State, Nigeria.Library Review, 52(8), 388-393.

Agbamu, J. U. (2000). Agricultural research-extension linkage systems: an international perspective. Network Paper-Agricultural Research and Extension Network, (106), 1-7.

Agranov, M., Bisin, A., & Schotter, A. (2014). An experimental study of the impact of competition for Other People's Money: the portfolio manager market. Experimental Economics, 17(4), 564-585.

Agwu, N. M., Nwankwo, E. E., & Anyanwu, C. I. (2014). Determinants of agricultural labour participation among youths in Abia State, Nigeria. International Journal of Food and Agricultural Economics, 2(1), 157-164.

Aiyelero, O. M., Kwanashie, H. O., Sheikh, T. L., & Hussaini, I. M. (2010) Mood Disorders and Their Management in A Nigerian Tertiary Health Institution. Journal of Hospital Pharmacists, 50, 1720-1723.

Akay, A., Martinsson, P., Medhin, H., & Trautmann, S. (2009). Attitudes toward uncertainty among the poor: evidence from rural Ethiopia. IZA Discussion Paper No. 4225

Akay, A., Martinsson, P., Medhin, H., & Trautmann, S. T. (2012). Attitudes toward uncertainty among the poor: an experiment in rural Ethiopia. Theory and Decision, 73(3), 453-464.

Alasia, A., Weersink, A., Bollman, R. D., & Cranfield, J. (2009). Off-farm labour decision of Canadian farm operators: Urbanization effects and rural labour market linkages. Journal of rural studies, 25(1), 12-24.

Albert, S. M., & Duffy, J. (2012). Differences in risk aversion between young and older adults. Neuroscience and neuroeconomics, 2012(1).

Alvarado, E., Ibanez, M., & Brummer, B. (2018). Understanding how risk preferences and social capital affect farmers' behavior to anticipatory and reactive adaptation options to climate change: the case of vineyard farmers in central Chile (No. 2058-2018-5286).

Amaefula, C., Okezie, C. A., & Mejeha, R. (2012). Risk attitude and insurance: a causal analysis. American Journal of Economics, 2(3), 26-32.

Anderson, L. R., & Mellor, J. M. (2009). Are risk preferences stable? Comparing an experimental measure with a validated survey-based measure.Journal of Risk and Uncertainty, 39(2), 137-160.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. Journal of the American statistical Association, 91(434), 444-455.

Anscombe, F. J., & Aumann, R. J. (1963). A definition of subjective probability. Annals of mathematical statistics, 34(1), 199-205.

Any Mental Illness (AMI) Among Adults. (n.d.). Retrieved September 6, 2016, from http://www.nimh.nih.gov/health/statistics/prevalence/any-mental-illness-ami-among-adults.shtm

Ariyabuddhiphongs, V. (2011). Lottery gambling: A review. Journal of Gambling Studies, 27(1), 15-33.

Arkes, H. R., Herren, L. T., & Isen, A. M. (1988). The role of potential loss in the influence of affect on risk-taking behavior. Organizational behavior and human decision processes, 42(2), 181-193.

Arkes, H. R., Herren, L. T., & Isen, A. M. (1988). The role of potential loss in the influence of affect on risk-taking behavior. Organizational behavior and human decision processes, 42(2), 181-193.

Asci, S., Borisova, T., & VanSickle, J. J. (2015). Role of economics in developing fertilizer best management practices. Agricultural Water Management, 152, 251-261.

Attanasio, Orazio, Abigail Barr, Juan Camilo Cardenas, Garance Genicot, and Costas Meghir (2012) 'Risk pooling , risk preferences , and social network' American Economic Journal: Applied Economics 4(2), 134–167

Aye, G. C., & Oji, K. O. (2007). Effect of Poverty on Risk Attitudes of Farmers in Benue State, Nigeria. In 12th Annual Conference on Econometric Modelling for Africa. Cape Town (pp. 4-6).

Azrieli, Y., Chambers, C. P., & Healy, P. J. (2018). Incentives in experiments: A theoretical analysis. Journal of Political Economy, 126(4), 1472-1503.

Babatunde, R. O. (2013). On-farm and off-farm works: complement or substitute?: evidence from rural nigeria. In 4th international conference of the African Association of Agricultural Economists.

Babatunde, R. O., & Qaim, M. (2009). The role of off-farm income diversification in rural Nigeria: Driving forces and household access. Quarterly Journal of International Agriculture, 48(4), 305-320.

Backus, D., Ferriere, A., & Zin, S. (2015). Risk and ambiguity in models of business cycles. Journal of Monetary Economics, 69, 42-63.

Backus, G. B. C., Eidman, V. R., & Dijkhuizen, A. A. (1997). Farm decision making under risk and uncertainty. NJAS wageningen journal of life sciences,45(2), 307-328.

Backus, G. B. C., Eidman, V. R., & Dijkhuizen, A. A. (1997). Farm decision making under risk and uncertainty. NJAS wageningen journal of life sciences, 45(2), 307-328.

Balcombe, K., & Fraser, I. (2015). Parametric preference functionals under risk in the gain domain: A Bayesian analysis. Journal of Risk and Uncertainty, 50(2), 161-187.

Balcombe, K., Fraser, I., & Chalak, A. (2009). Model selection in the Bayesian mixed logit: misreporting or heterogeneous preferences. J Environ Econ Manag, 57(2), 219-225.

Barberis, N., & Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. The American Economic Review, 98(5), 2066-2100.

Bard, S. K., & Barry, P. J. (2001). Assessing farmers' attitudes toward risk using the" closing-in" method. Journal of Agricultural and Resource Economics, 248-260

Bardhan, Dwaipayan, Y. P. S. Dabas, S. K. Tewari, and Avadhesh Kumar (2006). "An assessment of risk attitude of dairy farmers in Uttaranchal (India)." In Agricultural Economists Conference, August, pp. 12-18.

Baron, J. (2011). Risk attitude, investments, and the taste for luxuries versus necessities. Frontiers in psychology, 2.

Barrett, C. B. (1996). On price risk and the inverse farm size-productivity relationship. Journal of Development Economics, 51(2), 193-215.

Baslevent, C., & El-Hamidi, F. (2009). Preferences for early retirement among older government employees in Egypt. Economics Bulletin, 29(2), 554-565.

Battalio, R. C., Kagel, J. H., & Jiranyakul, K. (1990). Testing between alternative models of choice under uncertainty: Some initial results. Journal of risk and uncertainty, 3(1), 25-50.

Bauer, C., & Buchholz, W. (2008). How changing prudence and risk aversion affect optimal saving. CESifo Working Paper Series No. 2438. Available at SSRN: http://ssrn.com/abstract=1291112

Becker, Gordon M., M. H. DeGroot, and Jacob Marshak (1963), "An Experimental Study of Some Stochastic Models for Wagers," Behavioral Science, 3 (Summer), 199-202

Begum, M. A. A., & Manos, B. (2003). Farm planning under risk and uncertainty of a rural area in Bangladesh. NEW MEDIT (CIHEAM).

Bell, D. E. (1985). Putting a premium on regret. Management Science, 31, 117–120

Benazzi, F. (2007). Bipolar disorder—focus on bipolar II disorder and mixed depression. The Lancet, 369(9565), 935-945.

Berg, v. d. M. M. (2001). Off-farm income, risk, and agricultural production: a case study of smallholders in India's semi-arid tropics. s.n.], [S.l. Retrieved from http://library.wur.nl/WebQuery/wurpubs/122326

Bernoulli, D. (1954). Specimen theoriae novae de mensura sortis Commentarii academiae scientiarum imperiales petropolitanae, 5 (1738), pp. 175-192 Translated in Econometrica, 22 (1954), pp. 23-36

Best, M. J., & Grauer, R. R. (2011). Prospect-theory portfolios versus power-utility and mean–variance portfolios. Working paper, Beedie School of Business, Simon Fraser University.

Beyene, A. D. (2008). Determinants of off-farm participation decision of farm households in Ethiopia. Agrekon, 47(1), 140-161.

Bezabih, M., Gebreegziabher, Z., GebreMedhin, L., & Gunnar, K. (2010). Participation in off-farm employment, risk preferences, and weather variability: The Case of Ethiopia. Contributed Paper Presented at the Joint 3rd African Association of Agricultural Economies (AAAE), Cape Town, South Africa, 19-23.

Bezabih, M., Gebreegziabher, Z., GebreMedhin, L., & Gunnar, K. (2010). Participation in Off-Farm Employment, Risk Preferences, and Weather Variability: The Case of Ethiopia. Contributed Paper Presented at the Joint 3rd African Association of Agricultural Economies (AAAE), Cape Town, South Africa, 19-23.

Bezabih, M., Gebreegziabher, Z., GebreMedhin, L., & Köhlin, G. (2010). Participation in Off-Farm Employment, Rainfall Patterns, and Rate of Time Preferences: The Case of Ethiopia (No. dp-10-21-efd).

Bezu, S., & Holden, S. (2014). Are rural youth in Ethiopia abandoning agriculture?. World Development, 64, 259-272.

Bezu, S., S. Holden, and C.B. Barrett. 2009. Activity Choice in Rural Non-farm Employment: Survival versus Accumulation Strategy. Paper presented at the 8th Nordic Conference in Development Economics, 18–19 June 2009, Oscarsborg, Drobak, Norway.

Bhatta, B. P., & Arethun, T. (2013). Barriers to rural households' participation in low-skilled off-farm labor markets: Theory and empirical results from northern ethiopia. Springerplus, 2(1), 97.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural India. American journal of agricultural economics, 62(3), 395-407.

Binswanger, H. P., & Sillers, D. A. (1983). Risk aversion and credit constraints in farmers' decision-making: A reinterpretation. The Journal of Development Studies, 20(1), 5-21.

Blader, J. C., & Carlson, G. A. (2007). Increased rates of bipolar disorder diagnoses among US child, adolescent, and adult inpatients, 1996–2004. Biological psychiatry, 62(2), 107-114.

Blais, A. R., & Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. Judgment and Decision Making, 1(1).

Block, J., Sandner, P., & Spiegel, F. (2015). How do risk attitudes differ within the group of entrepreneurs? The role of motivation and procedural utility. Journal of Small Business Management, 53(1), 183-206.

Bocquého, G., Jacquet, F., & Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. European Review of Agricultural Economics, 41(1), 135-172.

Boehlje, M. D., & Trede, L. D. (1977). Risk management in agriculture. Journal of the American Society of Farm Managers and Rural Appraisers, 41(1), 20-29.

Bogan, V. L., Just, D. R., & Wansink, B. (2013). Do psychological shocks affect financial risk taking behavior? A study of US Veterans. Contemporary Economic Policy, 31(3), 457-467.

Boisvert, R. N., & Chang, H. (2006). Does Participation in the conservation reserve program and off-farm work affect the level and distribution of farm household incomes. In Selected Paper prepared for presentation at the American Agricultural Economic Association Annual Meetings, Long Beach, California.

Bolton, G. E., & Ockenfels, A. (2010). Betrayal aversion: Evidence from brazil, china, oman, switzerland, turkey, and the united states: Comment. American Economic Review, 100(1), 628-33.

Bolton, G. E., Ockenfels, A., & Stauf, J. (2015). Social responsibility promotes conservative risk behavior. European Economic Review, 74, 109-127.

Bond, G., & Wonder, B. (1980). Risk attitudes amongst Australian farmers. Australian Journal of Agricultural and Resource Economics, 24(1), 16-34.

Bontempo, R. N., Bottom, W. P., & Weber, E. U. (1997). Cross-cultural differences in risk perception: A model-based approach. Risk analysis, 17(4), 479-488.

Booij, A. S., Van Praag, B. M., & Van De Kuilen, G. (2010). A parametric analysis of prospect theory's functionals for the general population. Theory and Decision, 68(1-2), 115-148.

Booij, A. S., Van Praag, B. M., & Van De Kuilen, G. (2010). A parametric analysis of prospect theory's functionals for the general population. Theory and Decision, 68(1-2), 115-148.

Borch, K. (1969). A note on uncertainty and indifference curves. Rev. Econom. Stud. 36 1–4.

Borch, K. (1973). Expected utility expressed in terms of moments. Omega: The International Journal of Management Science 1 331–343.

Borch, K. (1974). The rationale of the mean–standard deviation analysis: Comment. American Economic Review 64 428–430.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2010). Salience theory of choice under risk (No. w16387). National Bureau of Economic Research.

Bougherara, D., Gassmann, X., Piet, L., & Reynaud, A. (2012, June). Eliciting farmers' risk and ambiguity preferences in the loss and gain. In 15. International Conference Foundations and Applications of Utility, Risk and Decision Theory (FUR) (pp. 12-p).

Bougherara, D., Gassmann, X., Piet, L., & Reynaud, A. (2017). Structural estimation of farmers' risk and ambiguity preferences: a field experiment. European Review of Agricultural Economics, 44(5), 782-808

Brick, K., Visser, M., & Burns, J. (2012). Risk aversion: experimental evidence from South African fishing communities. American Journal of Agricultural Economics, 94(1), 133-152.

Broomell, S. B., & Bhatia, S. (2014). Parameter recovery for decision modeling using choice data. Decision, 1(4), 252.

Bruhin, A., Fehr-Duda, H., & Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. Econometrica, 78(4), 1375-1412.

Brunette, M., Foncel, J., & Kéré, E. N. (2017). Attitude towards Risk and Production Decision: An Empirical analysis on French private forest owners. Environmental Modeling & Assessment, 22(6), 563-576.

BUI, (2009). Prospect Theory and Functional Choice (Doctoral dissertation, Bielefeld University, Germany).

Börjesson, M., Eliasson, J., & Franklin, J. P. (2012). Valuations of travel time variability in scheduling versus mean–variance models. Transportation Research Part B: Methodological, 46(7), 855-873.

Cabantous, L. (2007). Ambiguity aversion in the field of insurance: Insurers' attitude to imprecise and conflicting probability estimates. Theory and Decision, 62, 219–240.

Camerer, C., & Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. Journal of risk and uncertainty, 5(4), 325-370.

Campbell, D. (2006). Combining mixed logit models and random effects models to identify the determinants of willingness to pay for rural landscape improvements. In Proceedings of the 81 st Annual Conference of the Agricultural Economics Society.

Canales, E., Bergtold, J., Williams, J., & Peterson, J. (2015). Estimating farmers' risk attitudes and risk premiums for the adoption of conservation practices under different contractual arrangements: A stated choice experiment. In 2015 AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California (No. 205640). Agricultural and Applied Economics Association & Western Agricultural Economics Association.

Canning, P. (1992). Farm Buildings and Farmland: An Analysis of Capital Formation (No. 1800-1801). US Department of Agriculture, Economic Research Service.

Center for Substance Abuse Treatment. Managing Depressive Symptoms in Substance Abuse Clients During Early Recovery. Rockville (MD): Substance Abuse and Mental Health Services Administration (US); 2008. (Treatment Improvement Protocol (TIP) Series, No. 48.) Appendix D—DSM-IV-TR Mood Disorders. Available from: https://www.ncbi.nlm.nih.gov/books/NBK64063

Cervantes-Godoy, D., S. Kimura and J. Antón (2013), "Smallholder Risk Management in Developing Countries", OECD Food, Agriculture and Fisheries Papers, No. 61, OECD Publishing. http://dx.doi.org/10.1787/5k452k28wljl-en

Cettolin, E., & Tausch, F. (2015). Risk taking and risk sharing: Does responsibility matter?. Journal of Risk and Uncertainty, 50(3), 229-248.

Chakravarty, S., Harrison, G. W., Haruvy, E. E., & Rutström, E. E. (2011). Are you risk averse over other people's money?. Southern Economic Journal, 77(4), 901-913.

Chandler, R. A., Wakeley, J., Goodwin, G. M., & Rogers, R. D. (2009). Altered risk-aversion and risk-seeking behavior in bipolar disorder. Biological psychiatry, 66(9), 840-846.

Chandler, R. A., Wakeley, J., Goodwin, G. M., & Rogers, R. D. (2009). Altered risk-aversion and risk-seeking behavior in bipolar disorder. Biological psychiatry, 66(9), 840-846.

Charness, G., and A. Viceisza. (2012). "Comprehension and risk elicitation in the field: Evidence from rural Senegal." IFPRI Working Paper 01135, Wasgington DC

Charness, G., and Viceisza, A. (2015). Three risk-elicitation methods in the field: evidence from rural Senegal. Spelman College Faculty Publications. Paper 4.http://digitalcommons.auctr.edu/scpubs/4

Charness, G., Karni, E., & Levin, D. (2013). Ambiguity attitudes and social interactions: An experimental investigation. Journal of Risk and Uncertainty,46(1), 1-25.

Chateauneuf, A., & Cohen, M. (2000). Choquet expected utility model: A new approach to individual behavior under uncertainty and to social welfare. Fuzzy Measures and Integrals, 289-314.

Chauveau, T., & Nalpas, N. (2009). A theory of disappointment. ESC-Toulouse Working Papers.

Chavas, J. P. (2004). Risk analysis in theory and practice. Academic Press.

Cher, D. J., Miyamoto, J., & Lenert, L. A. (1997). Incorporating risk attitude into Markov-process decision models: importance for individual decision making. Medical Decision Making, 17(3), 340-350.

Chetty, R., Looney, A., & Kroft, K. (2009). Salience and taxation: Theory and evidence. The American economic review, 99(4), 1145-1177.

Chow, J. Y., Lee, G., & Yang, I. (2010). Estimating cumulative prospect theory parameters for HOV lane selection using genetic algorithm. In Washington DC: TRB 89th Annual Meeting.

Christopher, L. N. (2014). Analysis into the Factors influencing the Level of Small Scale Household Farmers' Off-Farm Income amongst the Grape Farmers in Dodoma Tanzania. International Research Journal of Social Sciences, 3(11), 8-16

Clarke, D., & Kalani, G. (2012). Microinsurance Decisions: Evidence From Ethiopia.

Clist, P., D'Exelle, B., & Verschoor, A. (2013). Nature's Frames, Reference Lotteries and Truly Risky Choice: Evidence from a Ugandan Field Lab.

Connors, R.D., & Sumalee, A. (2009) A network equilibrium model with travellers' perception of stochastic travel times. Transportation Research Part B: Methodological, 43 (6). 614 – 624.

Connors, RD and Sumalee, A (2009) A network equilibrium model with travellers' perception of stochastic travel times. Transportation Research Part B: Methodological, 43 (6). 614 – 624.

Cook, Joseph, Susmita Chatterjee, Dipika Sur, and Dale Whittington. "Measuring risk aversion among the urban poor in Kolkata, India." Applied Economics Letters 20, no. 1 (2013): 1-9. Available at SSRN: https://ssrn.com/abstract=1956178 or http://dx.doi.org/10.2139/ssrn.1956178

Coricelli, G., Diecidue, E., & Zaffuto, F. D. (2016). Aspiration Levels and Preference for Skewness in Choice Under Risk.

Coricelli, G., Diecidue, E., & Zaffuto, F. D. (2016). Aspiration Levels and Preference for Skewness in Choice Under Risk.

Couture, S., Reynaud, A., Dury, J., & Bergez, J. E. (2010). Farmer's risk attitude: Reconciliating stated and revealed preference approaches. In Fourth World Congress of Environmental and Resource Economists (pp. 10-2).

Couture, S., Reynaud, A., Dury, J., & Bergez, J. E. (2010). Farmer's risk attitude: reconciliating stated and revealed preference approaches. In Fourth World Congress of Environmental and Resource Economists (pp. 10-2).

Crosetto, P., & Filippin, A. (2013). A theoretical and experimental appraisal of five risk elicitation methods. Jena Economic Research Papers, 2013-009

Csermely, T., & Rabas, A. (2015). How to reveal people's preferences: Comparing time consistency and predictive power of multiple price list risk elicitation methods. Available at SSRN 2573544.

Dambacher, M., Haffke, P., Groß, D., & Hübner, R. (2016). Graphs versus numbers: How information format affects risk aversion in gambling. Judgment and Decision Making, 11(3), 223.

Damodaran, A. (2007). Strategic risk taking: a framework for risk management. Pearson Prentice Hall.

Dasgupta, U., Mani, S., Sharma, S., & Singhal, S. (2016). Eliciting Risk Preferences: Firefighting in the Field.

Davies, G. B., & Satchell, S. E. (2007). The behavioural components of risk aversion. Journal of Mathematical Psychology, 51(1), 1-13.

Davies, G. B., & Satchell, S. E. (2007). The behavioural components of risk aversion. Journal of Mathematical Psychology, 51(1), 1-13.

De Brauw, A., & Eozenou, P. (2014). Measuring risk attitudes among Mozambican farmers. Journal of Development Economics, 111, 61-74.

De Brauw, A., & Rozelle, S. (2008). Reconciling the returns to education in off-farm wage employment in rural China. Review of Development Economics, 12(1), 57-71.

Deck, C., Lee, J., Reyes, J., & Rosen, C. (2010). Measuring risk aversion on multiple tasks: Can domain specific risk attitudes explain apparently inconsistent behavior? 2010.

Deck, C. A., Lee, J., Reyes, J. A., & Rosen, C. (2008). Measuring risk attitudes controlling for personality traits. Available at SSRN 1148521.

De Filippo A., Han J., Newman-Martin C., Zeckhauser R., (2014). Deterrents to Insurance Purchases: Distrust and Zero Aversion Timothy Cheston, Working Paper – December

De Giorgi, E., & Hens, T. (2009). Prospect theory and mean-variance analysis: does it make a difference in wealth management. Investment Management and Financial Innovations, 6(1), 122.

De Janvry, A., & Sadoulet, E. (2001). Income strategies among rural households in Mexico: The role of off-farm activities. World development, 29(3), 467-480.

Delquié, P., & Cillo, A. (2006). Disappointment without prior expectation: a unifying perspective on decision under risk. Journal of Risk and Uncertainty, 33(3), 197-215.

De Palma, A., Ben-Akiva, M., Brownstone, D., Holt, C., Magnac, T., McFadden, D., ... & Walker, J. (2008). Risk, uncertainty and discrete choice models. Marketing Letters, 19(3-4), 269-285.

Dequech, D. (2000). Fundamental uncertainty and ambiguity. Eastern Economic Journal, 41-60.

Dertwinkel-Kalt, M., & Köster, M. (2015). Violations of first-order stochastic dominance as salience effects. Journal of Behavioral and Experimental Economics, 59, 42-46.

Diagnostic and Statistical Manual of Mental Disorders, (1994).Fourth Edition.

Diecidue, E., & Wakker, P. P. (2001). On the intuition of rank-dependent utility. Journal of Risk and Uncertainty, 23(3), 281-298.Washington, DC, American Psychiatric Association

Diggs, D. M. (1991). Drought experience and perception of climatic change among Great Plains farmers. Great Plains Research, 114-132.

Dillon, J. L., & Scandizzo, P. L. (1978). Risk attitudes of subsistence farmers in Northeast Brazil: A sampling approach. American Journal of Agricultural Economics, 60(3), 425-435.

Dimmock, S. G., Kouwenberg, R., & Wakker, P. P. (2015). Ambiguity attitudes in a large representative sample. Management Science.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2013).Ambiguity attitudes and economic behavior. National Bureau of Economic Research.

Dogan, D. (2008). Numerical optimization for mixed logit models and an application. ProQuest.

Domingo, S. N., Parton, K. A., Mullen, J., & Jones, R. (2015). Risk Aversion among Smallholder High-value Crop Farmers in the Southern Philippines (No. DP 2015-03).

Domingo, S. N., Parton, K. A., Mullen, J., & Jones, R. (2015). Risk aversion among smallholder high-value crop farmers in the southern Philippines.Philippine Institute for Development Studies, Discussion Paper Series N, 2015-03.

Donkers, B., Melenberg, B., & Van Soest, A. (2001). Estimating risk attitudes using lotteries: A large sample approach. Journal of Risk and Uncertainty,22(2), 165-195.

Donkers, B., Melenberg, B. and Van Soest, A. (2001) Estimating risk attitudes using lotteries: a large sample approach, Journal of Risk and Uncertainty, 22, 165–95

Douglas, E. J., & Shepherd, D. A. (2002). Self-employment as a career choice: Attitudes, entrepreneurial intentions, and utility maximization. Entrepreneurship Theory and Practice, 26(3), 81-90.

Dow, J., & da Costa Werlang, S. R. (1992). Uncertainty aversion, risk aversion, and the optimal choice of portfolio. Econometrica: Journal of the Econometric Society, 197-204.

Dugje, I.Y., Omoigui L.O., Ekeleme F, Kamara A.Y. & Ajeigbe H (2009). Farmers' Guide to Cowpea Production in West Africa. IITA, Ibadan, Nigeria. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.433.2839&rep=rep1&type=pdf

Duncan, M., & Prowse, C. (2014). Occupational therapy with mood disorders. Occupational Therapy in Psychiatry and Mental Health, 389-407.

Démurger, S., Fournier, M., & Yang, W. (2010). Rural households' decisions towards income diversification: Evidence from a township in northern China. China Economic Review, 21, S32-S44.

d'Acremont, M., & Bossaerts, P. (2008). Neurobiological studies of risk assessment: a comparison of expected utility and mean-variance approaches. Cognitive, Affective, & Behavioral Neuroscience, 8(4), 363-374.

Eckel, C. C., & Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. Evolution and human behavior, 23(4), 281-295.

Eckel, C. C., & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. Handbook of experimental economics results, 1, 1061-1073.

Economics Letters, 69:309-312.

Edmans, A., Garcia, D., & Norli, Ø. (2007). Sports sentiment and stock returns.The Journal of Finance, 62(4), 1967-1998.

Eichberger, J., Grant, S., & Kelsey, D. (2010). Comparing three ways to update Choquet beliefs. Economics Letters, 107(2), 91-94.

Ek, E., Remes, J., & Sovio, U. (2004). Social and developmental predictors of optimism from infancy to early adulthood. Social indicators research, 69(2), 219-242.

Eke-Göransson, C., & Rinman, M. (2012). Attitudes towards hedging by diversified and non-diversified farmers.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. The quarterly journal of economics, 643-669.

Erev, I., Ert, E., & Yechiam, E. (2008). Loss aversion, diminishing sensitivity, and the effect of experience on repeated decisions. Journal of Behavioral Decision Making, 21(5), 575-597.

Eriksen, K. W., & Kvaløy, O. (2009). Myopic investment management. Review of Finance, 14(3), 521-542.

Ert, E., & Erev, I. (2010). On the descriptive value of loss aversion in decisions under risk (No. 10-056). Harvard Business School.

Ert, E., & Erev, I. (2013). On the descriptive value of loss aversion in decisions under risk: Six clarifications. Judgment and Decision Making, 8(3), 214-235.

Etchart-Vincent, N., & l'Haridon, O. (2011). Monetary incentives in the loss domain and behavior toward risk: An experimental comparison of three reward schemes including real losses. Journal of Risk and Uncertainty, 42(1), 61-83.

Ettner, S.L., Frank, R.G., Kessler, R.C., 1997. The impact of psychiatric disorders on labor market outcomes. Industrial and Labor Relations Review 51 (1), 64–81

Eysenck, S. B., & Eysenck, H. J. (1977). The place of impulsiveness in a dimensional system of personality description. British Journal of Social and Clinical Psychology, 16(1), 57-68.

Fehr-Duda, H., Bruhin, A., Epper, T., & Schubert, R. (2010). Rationality on the rise: Why relative risk aversion increases with stake size. Journal of Risk and Uncertainty, 40(2), 147-180.

Fehr-Duda, H., Epper, T., Bruhin, A., & Schubert, R. (2011). Risk and rationality: The effects of mood and decision rules on probability weighting. Journal of Economic Behavior & Organization, 78(1), 14-24.

Fellner, G., & Maciejovsky, B. (2007). Risk attitude and market behavior: Evidence from experimental asset markets. Journal of Economic Psychology, 28(3), 338-350

Fellner, G., & Sutter, M. (2009). Causes, Consequences, and Cures of Myopic Loss Aversion–An Experimental Investigation*. The Economic Journal, 119(537), 900-916.

Fernandez-Cornejo, J., Mishra, A. K., Nehring, R. F., Hendricks, C., Southern, M., & Gregory, A. (2007). Off-farm income, technology adoption, and farm economic performance (No. 7234). United States Department of Agriculture, Economic Research Service.

Fishburn, P. C. (1984). SSB utility theory: An economic perspective. Mathematical Social Sciences, 8(1), 63-94.

Fossen, F. M., & Glocker, D. (2017). Stated and revealed heterogeneous risk preferences in educational choice. European Economic Review, 97, 1-25.

Fox, C.R., and Poldrack, R.A. (2008). Prospect theory and the brain. Chapter in Glimcher, P., Camerer, C., Fehr, E. & Poldrack, R. (Eds). Handbook of Neuroeconomics. New York: Elsevier.

Fox, C. R., Erner, C. & Walters, D. J. (2015). Decision Under Risk, in The Wiley Blackwell Handbook of Judgment and Decision Making (eds G. Keren and G. Wu), John Wiley & Sons, Ltd, Chichester, UK. doi: 10.1002/9781118468333.ch2

Frank, Richard and T. McGuire, "Economics and Mental Health," Handbook of Health Economics Vol. 1B, Culyer, A.J. and J.P. Newhouse (eds.), Elsevier, 2000

Freudenreich, H., Musshoff, O., & Wiercinski, B. (2017). The relationship between farmers' shock experiences and their uncertainty preferences-experimental evidence from Mexico(No. 92). GlobalFood Discussion Papers.

Frey, B. S., M. Benz, and A. Stutzer (2004). "Introducing Procedural Utility: Not Only What, but Also How Matters," Journal of Institutional and Theoretical Economics 160(3), 377–401.

Frisch, D., & Baron, J. (1988). Ambiguity and rationality. Journal of Behavioral Decision Making, 1(3), 149-157.

Fujino, J., Tei, S., Hashimoto, R. I., Itahashi, T., Ohta, H., Kanai, C., ... & Takahashi, H. (2017). Attitudes toward risk and ambiguity in patients with autism spectrum disorder. Molecular autism, 8(1), 45.

Funk, M., Drew, N., & Knapp, M. (2012). Mental health, poverty and development. Journal of public mental health, 11(4), 166-185.

Füllbrunn, S., & Luhan, W. J. (2015). Am I My Peer's Keeper? Social Responsibility in Financial Decision Making.

Galarza F. B. (2009) Choices under risk in rural Peru, Staff Paper No. 542, Madison University of Wisconsin

Geller, D. S., & Singer, J. D. (1998). Nations at war: a scientific study of international conflict (Vol. 58). Cambridge University Press.

Ghaemi, S. N., Miller, C. J., Berv, D. A., Klugman, J., Rosenquist, K. J., & Pies, R. W. (2005). Sensitivity and specificity of a new bipolar spectrum diagnostic scale. Journal of affective disorders, 84(2), 273-277.

Gilboa, I. (1987). Expected utility with purely subjective non-additive probabilities. Journal of mathematical Economics, 16(1), 65-88.

Giorgi, E., Hens, T., & Haim, L. (2004). Existence of CAPM Equilibria with Prospect Theory Preferences. National Center of Competence in Research Financial Valuation and Risk Management (No. 85, pp. 1-42). Working Paper.

Giorgi, E., Hens, T., & Haim, L. (2004). Existence of CAPM Equilibria with Prospect Theory Preferences. National Center of Competence in Research Financial Valuation and Risk Management (No. 85, pp. 1-42). Working Paper.

Glenn W. Harrison, E. Elisabet Rutström (2008), Risk Aversion in the Laboratory, in James C. Cox, Glenn W. Harrison (ed.) Risk Aversion in Experiments (Research in Experimental Economics, Volume 12) Emerald Group Publishing Limited, pp.41 – 196

Glöckner, A., & Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. Cognition, 123(1), 21-32.

Glöckner, A., & Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. Cognition, 123(1), 21-32.

Goetz, I., Tohen, M., Reed, C., Lorenzo, M., & Vieta, E. (2007). Functional impairment in patients with mania: baseline results of the EMBLEM study.Bipolar disorders, 9(1-2), 45-52.

Gong, Y., Baylis, K., Kozak, R., & Bull, G. (2016). Farmers' risk preferences and pesticide use decisions: evidence from field experiments in China. Agricultural Economics, 47(4), 411-421.

Gonzalez-Ramirez, J., Arora, P., & Podesta, G. (2018). Using Insights from Prospect Theory to Enhance Sustainable Decision Making by Agribusinesses in Argentina. Sustainability, 10(8), 2693.

Goodwin, B.K. & Bruer, S.M. (2003). An empirical analysis of farm structure and off-farm work decisions. Paper presented at AAEA annual meeting, Motreal, Canada

Goodwin, B. K., & Mishra, A. K. (2004). Farming efficiency and the determinants of multiple job holding by farm operators. American Journal of Agricultural Economics, 86(3), 722-729.

Gregg, D., & Rolfe, J. (2017). Risk behaviours and grazing land management: a framed field experiment and linkages to range land condition. Journal of Agricultural Economics, 68(3), 682-709.

Gummerum, M., Hanoch, Y., and Rolison, J. J. (2014). Offenders' risk-taking attitude inside and outside the prison walls. Risk Anal. 34, 1870–1881. doi: 10.1111/risa.12222

Gureje, O., Lasebikan, V. O., Kola, L., & Makanjuola, V. A. (2006). Lifetime and 12-month prevalence of mental disorders in the Nigerian Survey of Mental Health and Well-Being. The British Journal of Psychiatry, 188(5), 465-471.

Gómez-Limón, J. A., Riesgo, L., & Arriaza, M. (2002). Agricultural risk aversion revisited: a multicriteria decision-making approach. Zaragoza (Spain), 28, 31.

Gürtler, M., & Stolpe, J. (2011). Piecewise continuous cumulative prospect theory and behavioral financial engineering (No. IF37V1). Working papers//Institut für Finanzwirtschaft, Technische Universität Braunschweig.

Gürtler, M., & Stolpe, J. (2011). Piecewise Continuous Cumulative Prospect Theory and Piecewise Continuous Hedonic Framing. Available at SSRN 1965558.

Haffke, P., & Hübner, R. (2014). Effects of different feedback types on information integration in repeated monetary gambles. Frontiers in psychology, 5.

Halek, M., & Eisenhauer, J. G. (2001). Demography of risk aversion. Journal of Risk and Insurance, 1-24.

Halevy, Y. (2007). Ellsberg Revisited: An experimental study. Econometrica, 75, 503–536.

Haneishi, Y., Maruyama, A., Takagaki, M., & Kikuchi, M. (2014). Farmers' risk attitudes to influence the productivity and planting decision: A case of rice and maize cultivation in rural Uganda. African Journal of Agricultural and Resource Economics Volume, 9(4), 309-322.

Haneishi, Y., Maruyama, A., Takagaki, M., & Kikuchi, M. (2014). Farmers' risk attitudes to influence the productivity and planting decision: A case of rice and maize cultivation in rural Uganda. African Journal of Agricultural and Resource Economics Volume, 9(4), 309-322.

Haneishi, Y., Maruyama, A., Takagaki, M., & Kikuchi, M. (2014). Farmers' risk attitudes to influence the productivity and planting decision: A case of rice and maize cultivation in rural Uganda. African Journal of Agricultural and Resource Economics Volume, 9(4), 309-322.

Hanoch, Y., Johnson, J. G., and Wilke, A. (2006). Domain specificity in experimental measures and participant recruitment: an application to risktaking behavior. Psychol. Sci. 17, 300–304. doi: 10.1111/j.1467-9280.2006. 01702.x

Hansson, H., & Lagerkvist, C. J. (2012). Measuring farmers' preferences for risk: a domain-specific risk preference scale. Journal of Risk Research, 15(7), 737-753.

Hardaker, J. B. (Ed.). (2004). Coping with risk in agriculture. Cabi.

Hardaker, J. B., Huirne, R. B., Anderson, J. R., & Lien, G. (2004). Coping with risk in agriculture (No. Ed. 2). CABI publishing.

Hardaker, J. B., Huirne, R. B., Anderson, J. R., & Lien, G. (2004). Coping with risk in agriculture. New York: CAB International, 1997.

Harrison, G. W. (1989). Theory and misbehaviour of first-price auctions. The American Economic Review, 749-762.

Harrison, G. W. (2005). Hypothetical Bias Over Uncertain Outcomes. UCF Economics Working Paper No. 05-04. Available at SSRN: http://ssrn.com/abstract=698501 or http://dx.doi.org/10.2139/ssrn.698501

Harrison, G. W., & Swarthout, J. T. (2016). Cumulative prospect theory in the laboratory: A reconsideration. Center for the Economic Analysis of Risk, Working Paper, 2.

Harrison, G. W., Humphrey, S. J., & Verschoor, A. (2005). Choice under uncertainty in developing countries (No. 2005-18). CeDEx Discussion Paper, The University of Nottingham.

Harrison, G. W., Humphrey, S. J., & Verschoor, A. (2010). Choice under uncertainty: evidence from Ethiopia, India and Uganda*. The Economic Journal,120(543), 80-104.

Harrison, G. W., Lau, M. I., Rutström, E. E., & Tarazona-Gómez, M. (2012). Preferences over social risk. Oxford Economic Papers, 65(1), 25-46.

Harrison, Glenn W., and Rutström, E. Elisabet, "Representative Agents in Lottery Choice Experiments: One Wedding and A Decent Funeral," Working Paper 05-18, Department of Economics, College of Business Administration, University of Central Florida, 2005

Harvey, Nigel, Twyman, Matt & Harries, Clare (2006). Making Decisions for other People: The Problem of Judging Acceptable Levels of Risk [37 paragraphs]. Forum Qualitative Sozialforschung / Forum: Qualitative Social Research, 7(1), Art. 26, http://nbn-resolving.de/urn:nbn:de:0114-fqs0601266.

He, R., Jin, J., Gong, H., & Tian, Y. (2019). The role of risk preferences and loss aversion in farmers' energy-efficient appliance use behavior. Journal of Cleaner Production.

He, X. D., & Zhou, X. Y. (2011). Portfolio choice under cumulative prospect theory: An analytical treatment. Management Science, 57(2), 315-331.

Heifner, R., Coble, K., Perry, J., & Somwaru, A. (1999). Managing risk in farming: concepts, research, and analysis. US Department of Agriculture, Economic Research Service.

Henrich, J., & McElreath, R. (2002). Are Peasants Risk-Averse Decision Makers? 1. Current Anthropology, 43(1), 172-181.

Hens, T., & Rieger, M. O. (2010). Financial economics: A concise introduction to classical and behavioral finance. Springer Science & Business Media.

Hensher, D. A., & Greene, W. H. (2003). The mixed logit model: the state of practice. Transportation, 30(2), 133-176.

Hey, J. D., Lotito, G., & Maffioletti, A. (2007). Choquet OK?. Discussion Papers, Department of Economics and Related Studies University of York.

Holden, S., & Quiggin, J. (2015). Climate risk and state-contingent technology adoption: The role of risk preferences and probability weighting (No. 15-2015).

Holt, C. A., & Laury, S. K. (2005). Risk aversion and incentive effects: New data without order effects. American Economic Review, 902-904

Holtgraves, T., & Skeel, J. (1992). Cognitive biases in playing the lottery: Estimating the odds and choosing the numbers. Journal of Applied Social Psychology, 22(12), 934-952.

Hryshko, D., Luengo-Prado, M. J., & Sørensen, B. E. (2011). Childhood determinants of risk aversion: The long shadow of compulsory education: Childhood determinants of risk aversion. Quantitative Economics, 2(1), 37-72. doi:10.3982/QE2

Huber, O., Wider, R., & Huber, O.W. (1997). Active information search and complete information presentation in naturalistic risky decision tasks. Acta Psychologica, 95, 15–29

Huffman, W. E. (1980). Farm and off-farm work decisions: The role of human capital. The Review of Economics and Statistics, 14-23.

Huirne, R. B., Meuwissen, M. P., Hardaker, J. B., & Anderson, J. R. (2000). Risk and risk management in agriculture: an overview and empirical results.International Journal of Risk Assessment and Management, 1(1-2), 125-136.

Huirne, R. B., Meuwissen, M. P., Hardaker, J. B., & Anderson, J. R. (2000). Risk and risk management in agriculture: an overview and empirical results. International Journal of Risk Assessment and Management, 1(1-2), 125-136.

Humphrey, S. J., & Renner, E. (2011). The social costs of responsibility (No. 2011-02). CeDEx discussion paper series.

Humphrey, Steven J., (2000). "The Common Consequence Effect: Testing a Unified Explanation of Recent Mixed Evidence," Journal of Economic Behavior & Organization, 41, 239-262.

Ihli, H., Chiputwa, B., Bauermeister, G. F., & Musshoff, O. (2013). Measuring risk attitudes of smallholder farmers in Uganda: How consistent are results of different methods?. In The Second International Agricultural Risk, Finance, and Insurance Conference Paper.

Ihli, H. J., Chiputwa, B., & Musshoff, O. (2013). Do Changing Probabilities or Payoffs in Lottery-Choice Experiments Matter? Evidence from Rural Uganda(No. 24). GlobalFood Discussion Papers.

Ihli, H. J., Chiputwa, B., & Musshoff, O. (2016). Do changing probabilities or payoffs in lottery-choice experiments affect risk preference outcomes? Evidence from rural Uganda. Journal of Agricultural and Resource Economics, 41(2), 324.

Institute for Health Metrics and Evaluation (IHME), 2017. Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2016 (GBD 2016) Results. Seattle, United States.

International Institute of Tropical Agriculture (IITA) (2013). Retrived from http://www.iita.org/2013-press-releases/-/asset_publisher/CxA7/content/nigeria-releases-improved-cassava-varieties-to-boost-productivity?redirect=%2F2013-press-releases#.WAdoTPkrLcs

International Labour Organization, ILOSTAT database. Data retrieved in November 2017.

Iqbal, M. A., Ping, Q., Abid, M., Kazmi, S. M. M., & Rizwan, M. (2016). Assessing risk perceptions and attitude among cotton farmers: A case of Punjab province, Pakistan. International Journal of Disaster Risk Reduction,16, 68-74.

Irwin, J. R., McClelland, G. H., & Schulze, W. D. (1992). Hypothetical and real consequences in experimental auctions for insurance against low-probability risks. Journal of Behavioral Decision Making, 5(2), 107-116.

Isaac, R. M., & James, D. (2000). Just who are you calling risk averse?.Journal of Risk and Uncertainty, 20(2), 177-187.

Isen, A. M., & Geva, N. (1987). The influence of positive affect on acceptable level of risk: The person with a large canoe has a large worry. Organizational Behavior and Human Decision Processes, 39(2), 145-154.

Isen, A. M., & Geva, N. (1987). The influence of positive affect on acceptable level of risk: The person with a large canoe has a large worry. Organizational Behavior and Human Decision Processes, 39(2), 145-154.

Isik, M. (2002). Resource management under production and output price uncertainty: implications for environmental policy. American Journal of Agricultural Economics, 84(3), 557-571.

Islam N (1997). The Nonfarm Sector and Rural Development : Review of Issues and Evidence, A 2020 Vision for Food, Agriculture and the Environment, IFPRI, Washington, DC, USA.

Jacobson, S., & Petrie, R. (2007). Inconsistent Choices in Lottery Experiments: Evidence from Rwanda. Journal of Risk and Uncertainty.

Jacobson, S., & Petrie, R. (2009). Learning from mistakes: What do inconsistent choices over risk tell us?. Journal of Risk and Uncertainty,38(2), 143-158.

Jamison, Kay Redfield, Touched with Fire, New York: Simon and Schuster, 1993

Jehle, G. A., & Reny, P. J. Advanced Microeconomic Theory, 2001 2nd edition (Boston: Addison Wesley).

Jidda, M. S., Wakil, M. A., Ibrahim, A. W., & Mohammed, A. O. (2014). An investigation into the relationship between first-degree relatives of bipolar affective disorder and (idiopathic) epilepsy in a sub-Saharan African population.Journal of affective disorders, 161, 84-86.

Jin, H., & Yu Zhou, X. (2008). Behavioral portfolio selection in continuous time. Mathematical Finance, 18(3), 385-426.

Johnson, S. L., Carver, C. S., & Gotlib, I. H. (2012). Elevated ambitions for fame among persons diagnosed with bipolar I disorder. Journal of Abnormal Psychology, 121(3), 602.

Josephs, R. A., Larrick, R. P., Steele, C. M., & Nisbett, R. E. (1992). Protecting the self from the negative consequences of risky decisions. Journal of personality and social psychology, 62(1), 26.

Jung, S. (2013). Does Education Affect Risk Aversion?: Evidence from the 1973 British Education Reform. PSE Working Papers n2014-13.

Kaan, D. (1998). Defining Risk and a Framework for Moving Towards Resilience In Agriculture. Risk and Resilience Agriculture Series.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. American Economic Review, 324-343.

Kardes, F. R. (1994). Consumer judgment and decision processes. Handbook of social cognition, 2, 399-466.

Karmarkar, U. S. (1978). Subjectively weighted utility: A descriptive extension of the expected utility model. Organizational Behavior and Human Performance, 21(1), 61-72. doi:10.1016/0030-5073(78)90039-9

Kathleen Holmes, M., Bearden, C. E., Barguil, M., Fonseca, M., Serap Monkul, E., Nery, F. G., ... & Glahn, D. C. (2009). Conceptualizing impulsivity and risk taking in bipolar disorder: importance of history of alcohol abuse. Bipolar Disorders, 11(1), 33-40.

Kebede, Y., Gunjal, K., & Coffin, G. (1990). Adoption of new technologies in Ethiopian agriculture: the case of Tegulet-Bulga district Shoa province.Agricultural economics, 4(1), 27-43.

Kercheval, A. N. (2012). Financial Economics: A Concise Introduction to Classical and Behavioral Finance, by T. Hens and MO Rieger. Springer, Heidelberg (2012) ISBN 978-3-540-36148-0.

Kibet, N., Obare, G. A., & Lagat, J. K. (2018). Risk attitude effects on Global-GAP certification decisions by smallholder French bean farmers in Kenya. Journal of Behavioral and Experimental Finance, 18, 18-29.

King A. G. (1974): "Occupational Choice, Risk Aversion, and Wealth," Industrial and Labor Relations Review. Vol. 27, No. 4 (Jul., 1974), 586-596.

Kliger, D., & Kudryavtsev, A. (2014). Out of the blue: mood maintenance hypothesis and seasonal effects on investors' reaction to news. Quantitative Finance, 14(4), 629-640.

Kontek, K. (2009) Lottery Valuation Using the Aspiration/Relative Utility Function. Warsaw School of Economics, Department of Applied Econometrics Working Paper No. 5-09. Available at SSRN: https://ssrn.com/abstract=1437420 or http://dx.doi.org/10.2139/ssrn.1437420

Kothiyal, A., Spinu, V., & Wakker, P. P. (2011). Prospect theory for continuous distributions: A preference foundation. Journal of Risk and Uncertainty, 42(3), 195-210.

Kouame, E., & Komenan, A. (2012). Risk preferences and demand for insurance under price uncertainty: An experimental approach for cocoa farmers in Côte d'Ivoire. ILO Microinsurance Innovation Facility Research Paper, (13).

Kouame, E. B. H. (2010). Risk, risk aversion and choice of risk management strategies by cocoa farmers in western Cote D. Ivoire', University of Cocody–AERC Collaborative PhD Program, Abidjan.

Kroll, E. B., & Vogt, B. (2008). Attraction to Chance in Germany and Australia. An experimental study of cultural differences (No. 08006). Otto-von-Guericke University Magdeburg, Faculty of Economics and Management.

Kroll, Y., Levy, H., & Rapoport, A. (1988). Experimental tests of the mean-variance model for portfolio selection. Organizational Behavior and Human Decision Processes, 42(3), 388-410.

Kruschke, J. K. and Vanpaemel, W. (2015). Bayesian estimation in hierarchical models. In: J. R. Busemeyer, Z. Wang, J. T. Townsend, and A. Eidels (Eds.), The Oxford Handbook of Computational and Mathematical Psychology, pp. 279-299. Oxford, UK: Oxford University Press

Kunreuther, H. (1996). Mitigating disaster losses through insurance. Journal of risk and Uncertainty, 12(2), 171-187.

Kunreuther, H., & Wright, G. (1979). Safety-first, gambling, and the subsistence farmer. In J. A. Roumasset, J.-M. Boussard, & I. Singh (Eds.), Risk, uncertainty, and agricultural development (pp. 213-230). New York, NY: Agricultural Development Council.

Kurnianingsih, Y. A., Sim, S. K., Chee, M. W., & Mullette-Gillman, O. (2015). Aging and loss decision making: increased risk aversion and decreased use of maximizing information, with correlated rationality and value maximization. Frontiers in human neuroscience, 9, 280.

Kvaløy, O., & Luzuriaga, M. (2014). Playing the trust game with other people's money. Experimental Economics, 17(4), 615-630.

Köbberling, V., & Wakker, P. P. (2005). An index of loss aversion. Journal of Economic Theory, 122(1), 119-131.

Kühberger, A., Schulte-Mecklenbeck, M., & Perner, J. (2002). Framing decisions: Hypothetical and real. Organizational Behavior and Human Decision Processes, 89(2), 1162-1175.

Lagerkvist, C., Larsen, K. & Olson, K. (2006). Off-farm income and farm capital accumulation: a farmlevel data analysis. Annual Meeting of the American Agricultural Economics Association, California, 22pp.

Lamb, R. L. (2003). Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. American Journal of Agricultural Economics, 85(2), 359-371.

Lammers, J., Willebrands, D., & Hartog, J. (2010). Risk attitude and profits among small enterprises in Nigeria (No. 10-053/3). Tinbergen Institute.

Leahy, R. L. (1999). Decision making and mania. Journal of Cognitive Psychotherapy, 13(2), 83-105.

Leahy, R. L. (1999). Decision Making and Mania1. Journal of Cognitive Psychotherapy, 13(2), 83.

Lepori, G. M. (2010). Positive mood, risk attitudes, and investment decisions: field evidence from comedy movie attendance in the US. Risk Attitudes, and Investment Decisions: Field Evidence from Comedy Movie Attendance in the US

Lepori, G. M. (2010). Positive mood, risk attitudes, and investment decisions: Field evidence from comedy movie attendance in the US. Risk Attitudes, and Investment Decisions: Field Evidence from Comedy Movie Attendance in the US (October 11, 2010).

Levy, H., & Levy, M. (2003). Prospect theory and mean-variance analysis. Review of Financial Studies, 17(4), 1015-1041.

Levy, M., & Benita, G. (2009). Are Equally Likely Outcomes Perceived as Equally Likely?. The Journal of Behavioral Finance, 10(3), 128-137.

Levy, M., & Levy, H. (2002). Prospect Theory: Much Ado about Nothing? Management Science, 48(10), 1334-1349. Retrieved from http://www.jstor.org/stable/822640

Liebenehm, S., & Waibel, H. (2014). Simultaneous estimation of risk and time preferences among small-scale cattle farmers in West Africa. American Journal of Agricultural Economics, 96(5), 1420-1438.

Lien, D. D., & Yu, C. F. J. (2014). Production and Hedging under Ambiguity: A Choquet Expected Utility Analysis. Available at SSRN 2476883.

Lion, R., & Meertens, R. M. (2001). Seeking Information About a Risky Medicine: Effects of Risk-Taking Tendency and Accountability. Journal of Applied Social Psychology, 31(4), 778-795.

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. Review of Economics and Statistics, 95(4), 1386-1403.

Liu, E. M., & Huang, J. (2013). Risk preferences and pesticide use by cotton farmers in China. Journal of Development Economics, 103, 202-215.

Lobel, R. E., Klotzle, M. C., SILVA, P. V. J. D. G., & PINTO, A. C. F. (2017). PROSPECT THEORY: A PARAMETRIC ANALYSIS OF FUNCTIONAL FORMS IN BRAZIL. Revista de Administração de Empresas, 57(5), 495-509.

Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. The economic journal, 92(368), 805-824.

Loomes, G., & Sugden, R. (1983). A rationale for preference reversal. The American Economic Review, 73(3), 428-432.

Loughrey, J., Hennessy, T., Hanrahan, K., Donnellan, T., Raimondi, V., & Olper, A. (2013). Determinants of Farm Labour Use: A Comparison between Ireland and Italy: International Agricultural Trade Research Consortium.

Love, A., Magnan, N., & Colson, G. J. (2014). Male and Female Risk Preferences and Maize Technology Adoption in Kenya. In 2014 Annual Meeting, July 27-29, 2014, Minneapolis, Minnesota (No. 170241). Agricultural and Applied Economics Association.

Love, A., Magnan, N., & Colson, G. J. (2014). Male and female risk preferences and maize technology adoption in Kenya. In Selected Paper Prepared for Presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting. Minneapolis, MN, July (pp. 27-29).

Luce, D. (1959). Individual Choice Behavior, New York: John Wiley & Sons.

Ludvig, E. A., Madan, C. R., & Spetch, M. L. (2014). Extreme outcomes sway risky decisions from experience. Journal of Behavioral Decision Making, 27(2), 146-156.

Machina, M. J., & Schmeidler, D. (1992). A more robust definition of subjective probability. Econometrica: Journal of the Econometric Society, 745-780.

Madalla, G. (1983). Limited-dependent and qualitative variables in econometrics. New York: CambridgeUniversity PressMadallaLimited-dependent and qualitative variables in econometrics1983.

Madan, C. R., Ludvig, E. A., & Spetch, M. L. (2014). Remembering the best and worst of times: Memories for extreme outcomes bias risky decisions.Psychonomic bulletin & review, 21(3), 629-636.

Maertens, A., Chari, A. V., & Just, D. R. (2014). Why Farmers Sometimes Love Risks: Evidence from India. Economic Development and Cultural Change,62(2), 239-274.

Man, N. (2009). Factors affecting the decision making in off farm employment among paddy farmers in Kemasin Semerak. Pertanika Journal of Social Sciences & Humanities, 17(1), 7-15.

Mangelsdorff, L., & Weber, M. (1994). Testing Choquet expected utility. Journal of Economic Behavior & Organization, 25(3), 437-457.

Mao, Q., Wang, W., Oniki, S., Kagatsume, M., & Yu, J. (2016). Experimental Measure of Rural Household Risk Preference: The Case of the SLCP Area in Northern Shaanxi, China. Japan Agricultural Research Quarterly: JARQ, 50(3), 253-265.

Marcotte, D.E., Wilcox-Go¨k, V., Redmon, D.P., 2000. The labor market effects of mental illness: the case of affective disorders. In: Sorkin, A. (Ed.), Research in Human Capital and Development, vol. 13. JAI Press Inc., Stamford, Conn..

Mariel, P., De Ayala, A., Hoyos, D., & Abdullah, S. (2013). Selecting random parameters in discrete choice experiment for environmental valuation: a simulation experiment. Journal of choice modelling, 7, 44-57.

Markowitz, H. (1952). Portfolio selection. The journal of finance, 7(1), 77-91.

Marra, M., Pannell, D. J., & Ghadim, A. A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve?. Agricultural systems, 75(2), 215-234.

Martino, D. J., Strejilevich, S. A., Torralva, T., & Manes, F. (2011). Decision making in euthymic bipolar I and bipolar II disorders. Psychological Medicine, 41(6), 1319-1327.

Mas-Colell, A., Whinston, M. D., & Green, J. R. (1995). Microeconomic theory (Vol. 1). New York: Oxford university press.

Mason, L., O'Sullivan, N., Montaldi, D., Bentall, R. P., & El-Deredy, W. (2014). Decision-making and trait impulsivity in bipolar disorder are associated with reduced prefrontal regulation of striatal reward valuation. Brain, awu152.

Mattos, F., Garcia, P., & Pennings, J. M. (2007). Insights into trader behavior: Risk aversion and probability weighting. In Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL.

Mayraz, G. (2014). Priors and Desires: a Model of Optimism, Pessimism, and Cognitive Dissonance.

McCarthy, N., & Sun, Y. (2009). Participation by men and women in off-farm activities: An empirical analysis in rural Northern Ghana (Vol. 852). Intl Food Policy Res Inst.

McCaskey, M. B. (1982). The executive challenge: Managing change and ambiguity. Harpercollins College Div.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. Journal of applied Econometrics, 15(5), 447-470.

McNamara, K. T., & Weiss, C. R. (2001). On-and off-farm diversification. AAEA.

McNamara, K. T., & Weiss, C. R. (2001). On-and off-farm diversification. AAEA.

Mduma, J., and P. Wobst. 2005. Determinants of Rural Labor Market Participation in Tanzania. African Studies Quarterly 8(2)

Mduma, J. K. (2014). Gender Differences in Rural Off-farm Employment Participation in Tanzania: Is Spatial Mobility an Issue? African Journal of Economic Review, 2(1), 3-24.

Mellers, B. A., Schwartz, A., & Weber, E. U. (1997). Do risk attitudes reflect in the eye of the beholder?.

Menapace, L., Colson, G., & Raffaelli, R. (2012). Cognitive heuristics and farmers' perceptions of risks related to climate change. In 2012 Annual Meeting, August 12–14, 2012, Seattle, Washington (Vol. 124770, No. 12, p. 08).

Menapace, L., Colson, G., & Raffaelli, R. (2015). A comparison of hypothetical risk attitude elicitation instruments for explaining farmer crop insurance purchases. European Review of Agricultural Economics, 43(1), 113-135.

Mengel, F., Tsakas, E., & Vostroknutov, A. (2011). Decision making with imperfect knowledge of the state space. METEOR, Maastricht research school of Economics of TEchnology and ORganizations.

Mengel, F., Tsakas, E., & Vostroknutov, A. (2012). An Experiment on How Past Experience of Uncertainty Affects Risk Preferences.

Mengel, F., Tsakas, E., & Vostroknutov, A. (2016). Past experience of uncertainty affects risk aversion. Experimental Economics, 19(1), 151-176.

Meraner, M., & Finger, R. (2017). Risk perceptions, preferences and management strategies: evidence from a case study using German livestock farmers. Journal of Risk Research, 1-26.

Mersinas, K., Hartig, B., Martin, K. M., & Seltzer, A. (2015). Experimental Elicitation of Risk Behaviour amongst Information Security Professionals. In Workshop on the Economics of Information Security (WEIS).

Merton, R. C. (1971). Optimum consumption and portfolio rules in a continuous-time model. Journal ofEconomic Theory, 3, 373–413.

Meyerson, D., & Martin, J. (1987). Cultural change: An integration of three different views [1]. Journal of management studies, 24(6), 623-647..

Michenaud, S., & Solnik, B. (2008). Applying regret theory to investment choices: Currency hedging decisions. Journal of International Money and Finance, 27(5), 677-694.

Miller, P. M., Fagley, N. S., & Casella, N. E. (2009). Effects of problem frame and gender on principals' decision making. Social Psychology of Education, 12(3), 397-413.

Mishra, A. K., & Goodwin, B. K. (1997). Farm income variability and the supply of off-farm labor. American Journal of Agricultural Economics, 79(3), 880-887.

Miyata, S. (2003). Household's risk attitudes in Indonesian villages. Applied Economics, 35(5), 573-583.

Mohammed, A. O. (2014). An investigation into the relationship between first-degree relatives of bipolar affective disorder and (idiopathic) epilepsy in a sub-Saharan African population.Journal of affective disorders, 161, 84-86.

Mumford, J. D., & Norton, G. A. (1984). Economics of decision making in pest management. Annual review of entomology, 29(1), 157-174.

Musetescu R., Paun C., Brasoveanu I., & A., Draghici (2007): „Empirical evidence on riskn aversion for the Romanian capital market investors", Working paper no. 59

Nagengast, A. J., Braun, D. A., & Wolpert, D. M. (2011). Risk-sensitivity and the mean-variance trade-off: decision making in sensorimotor control. Proceedings of the Royal Society of London B: Biological Sciences, rspb20102518

Nagengast, A. J., Braun, D. A., & Wolpert, D. M. (2011). Risk-sensitivity and the mean-variance trade-off: decision making in sensorimotor control. Proceedings of the Royal Society of London B: Biological Sciences, rspb20102518.

Nan, X. (2007). Social distance, framing, and judgment: A construal level perspective. Human Communication Research, 33(4), 489-514.

Nardon, M., & Pianca, P. (2014). European option pricing with constant relative sensitivity probability weighting function. University Ca' Foscari of Venice, Dept. of Economics Working Paper Series No. 25/WP/2014. Available at SSRN: https://ssrn.com/abstract=2539085 or http://dx.doi.org/10.2139/ssrn.2539085

Navarro, D. J., Griffiths, T. L., Steyvers, M., & Lee, M. D. (2006). Modeling individual differences using Dirichlet processes. Journal of mathematical Psychology, 50(2), 101-122.

Negash A, Alem A, Kebede D, Deyessa N, Shibre T, Kullgren G (2005). Prevalence and clinical characteristics of bipolar I disorder in Butajira, Ethiopia: A community-based study. Journal of Affective Disorders 87, 193-20

Neilson, W. S. (2001). Calibration results for rank-dependent expected utility. Economics Bulletin, 4(10), 1-5.

Newell, A., & Simon, H. A. (1972). Human problem solving (Vol. 104, No. 9). Englewood Cliffs, NJ: Prentice-Hall.

Nguyen, N. C., Wegener, M., Russell, I., Cameron, D., Coventry, D., & Cooper, I. (2007). Risk management strategies by Australian farmers: two case studies.

NHS (2011). Bipolar disorder. Available from: https://www.nhs.uk/conditions/bipolar-disorder/ [Accessed 28 October 2016].

Nicholson, N., Soane, E., Fenton-O'Creevy, M., & Willman, P. (2005). Personality and domain-specific risk taking. Journal of Risk Research, 8(2), 157-176.

Nilsson, H., Rieskamp, J., & Wagenmakers, E. J. (2011). Hierarchical Bayesian parameter estimation for cumulative prospect theory. Journal of Mathematical Psychology, 55(1), 84-93.

Nmadu, J. N., Eze, G. P., & Jirgi, A. J. (2012). Determinants of risk status of small scale farmers in Niger State, Nigeria. Methodology.

Nwankwo, U. M., & Wolfgang, B. (2008). The Effect of Information and Market Access on Adopters' Income Level. Income Stabilization in a Changing Agricultural World: policy and tools. Warsaw: Wies Jutra Limited, 140-157.

Ogisi O.D., Begho T. & Bennet, O. A. (2013). Gender Roles in the Productivity and Profitability of Cassava (Manihot Esculenta) in Ika South and Ika North East Local Government Areas of Delta State, Nigeria. World Applied Sciences Journal, 24(12), 1610-1615.

Ogoke, U. P., Nduka, E. C., & Nja, M. E. (2015). Bipolar Disorder Investigation Using Modified Logistic Ridge Estimator. IOSR Journal of Mathematics (IOSR-JM) e-ISSN: 2278-5728, p-ISSN: 2319-765X. Volume 11, Issue 1 Ver. III PP 12-15 www.iosrjournals.org

Olarinde, L. O., Manyong, V. M., & Akintola, J. O. (2007). Attitudes towards risk among maize farmers in the dry savanna zone of Nigeria: some prospective policies for improving food production. African Journal of Agricultural Research, 2(8), 399-408.

Olarinde, L. O., Manyong, V. M., & Akintola, J. O. (2010). Factors influencing risk aversion among maize farmers in the Northern Guinea Savanna of Nigeria: Implications for sustainable crop development programmes. Journal of Food, Agriculture & Environment, 8(1), 128-134.

Olubiyo, S. O., Hill, G. P., & Webster, J. P. G. (2009). Econometric analysis of the impact of agricultural insurance of farming systems in the middle belt, Nigeria. African Journal of Food, Agriculture, Nutrition and Development, 9(6).

Onyeama, M., Agomoh, A., & Jombo, E. (2010). Bipolar disorder in Enugu, South East Nigeria: demographic and diagnostic characteristics of patients. Psychiatr Danub, 22(Suppl 1), S152-S157.

Onyemelukwe, C. (2016). Stigma and mental health in Nigeria: Some suggestions for law reform. JL Pol'y & Globalization, 55, 63.

Orhan G ,Vedat C ,Ahmet A ,Zeki B , (2016). Determinants of Farmers' Risk Aversion in Apricot Production in Turkey. International Journal of Management and Applied Science (IJMAS) , pp. 149-155, Volume-2,Issue-9

Oyewunmi, A. E., Oyewunmi, O. A., Iyiola, O. O., & Ojo, A. Y. (2015). Mental health and the Nigerian workplace: Fallacies, facts and the way forward. International Journal of Psychology, 7(7), 106-111.

Pachur, T., Suter, R. S., & Hertwig, R. (2017). How the twain can meet: Prospect theory and models of heuristics in risky choice. Cognitive Psychology, 93, 44-73.

Pahlke, J., Strasser, S., & Vieider, F. M. (2015). Responsibility effects in decision making under risk. Journal of Risk and Uncertainty, 51(2), 125-146.

Pang, X., Kuang, Y., & Gong, X. (2014). Rural Household's Risk Attitude and Credit Rationing: The Case of Chongqing in China. American Journal of Industrial and Business Management, 4(12), 728.

Patrick, G. F. (1998). Managing risk in agriculture. Midwest Plan Service.

Pattillo, C., & Söderbom, M. (2000). Managerial risk attitudes and firm performance in Ghanaian manufacturing: An empirical analysis based on experimental data. University of Oxford, Institute of Economics and Statistics, Centre for the Study of African Economies.

Paunonen, S. V., & Jackson, D. N. (1996). The Jackson Personality Inventory and the five-factor model of personality. Journal of Research in Personality,30(1), 42-59.

Payne, J. W. (2005). It is whether you win or lose: The importance of the overall probabilities of winning or losing in risky choice. Journal of Risk and Uncertainty, 30(1), 5-19.

Payne, J. W. (2005). It is whether you win or lose: The importance of the overall probabilities of winning or losing in risky choice. Journal of Risk and Uncertainty, 30(1), 5-19.

Pennings, J. M., & Garcia, P. (2001). Measuring producers' risk preferences: a global risk-attitude construct. American Journal of Agricultural Economics,83(4), 993-1009.

Petraud, J., Boucher, S., & Carter, M. (2015). Competing theories of risk preferences and the demand for crop insurance: Experimental evidence from Peru. In 2015 Conference, August 9-14, 2015, Milan, Italy (No. 211383). International Association of Agricultural Economists.

Pfeiffer, L., López-Feldman, A., & Taylor, J. E. (2009). Is off-farm income reforming the farm? Evidence from Mexico. Agricultural Economics, 40(2), 125-138.

Pirvu, T. A., & Schulze, K. (2012). Multi-stock portfolio optimization under prospect theory. Mathematics and Financial Economics, 1-26.

Pollmann, M. M., Potters, J., & Trautmann, S. T. (2014). Risk taking by agents: The role of ex-ante and ex-post accountability. Economics Letters, 123(3), 387-390.

Polman, E. (2012). Self–other decision making and loss aversion. Organizational Behavior and Human Decision Processes, 119(2), 141-150.

Polman, Evan, and Kathleen Vohs. "When Choosing For Others Is More Fun (And Less Depleting) Than Choosing For the Self." NA-Advances in Consumer Research Volume 42 (2014).

Prelec, D. (1998). The probability weighting function. Econometrica, 497-527.

Rachlinski, J.J. (2000). “The Psychology of Global Climate Change,” University of Illinois Law Review 299:303-313

Rahman, M. S. (2013). Socio-economic determinants of off-farm activity participation in Bangladesh. Russian Journal of Agricultural and Socio-Economic Sciences, 13(1).

Raimondi, V., Curzi, D., Bertoni, D., & Olper, A. (2013). Off-farm Labour Decision of Italian Farm Operators (No. 157120).

Ramaratnam, S., Rister, J. E., Bessler, D. A., & Novak, J. (1986). Risk attitudes and farm/producer attributes: a case study of Texas Coastal Bend grain sorghum producers. Journal of Agricultural and Applied Economics, 18(2), 85.

Ranganathan, T., Gaurav, S., & Singh, A. (2014) Anomaly in Decision Making Under Risk: Violation of Stochastic Dominance Among Farmers in Gujarat, India. IEG Working Paper No. 343

Reddy, L. F., Lee, J., Davis, M. C., Altshuler, L., Glahn, D. C., Miklowitz, D. J., & Green, M. F. (2014). Impulsivity and risk taking in bipolar disorder and schizophrenia. Neuropsychopharmacology, 39(2), 456-463.

Reid, J. D. (1976). Sharecropping and agricultural uncertainty. Economic Development and Cultural Change, 549-576.

Reij, C., & Waters-Bayer, A. (2001). Farmer innovation in Africa: a source of inspiration for agricultural development. Earthscan.

Resende, J. G. L., & Tecles, P. L. (2011) A Simple Method of Elicitation of Preferences under Risk. Brazilian Review of Econometrics, 31(2), 201-229.

Reynaud, A., & Couture, S. (2012). Stability of risk preference measures: results from a field experiment on French farmers. Theory and decision,73(2), 203-221.

Reynolds, D. B., Joseph, J., & Sherwood, R. (2011). Risky shift versus cautious shift: determining differences in risk taking between private and public management decision-making. Journal of Business & Economics Research (JBER), 7(1).

Richard, R., Pligt, J., & Vries, N. K. (1996). Anticipated regret and time perspective: Changing sexual risk-taking behavior. Journal of Behavioral Decision Making, 9, 185-199.

Rieger, M. O., & Bui, T. (2010). Too risk-averse for prospect theory?(December 16, 2010). Available at SSRN: https://ssrn.com/abstract=1772605 or http://dx.doi.org/10.2139/ssrn.1772605

Rieger, M. O., & Wang, M. (2008). Prospect theory for continuous distributions.Journal of Risk and Uncertainty, 36(1), 83-102.

Rieger, M. O., Wang, M., & Hens, T. (2014). Estimating cumulative prospect theory parameters from an international survey. Theory and Decision, 1-30.

Roe, B., E. (2015), The Risk Attitudes of U.S. Farmers, Applied Economic Perspectives and Policy, Volume 37, Issue 4, Pages 553–574

Rohrmann, B. (2005). Risk attitude scales: concepts, questionnaires, utilizations. Project report. Online access http://www. rohrmannresearch. net/pdfs/rohrmann-ras-report. pdf, 13, 2012.

Rolfo, J. (1980). Optimal hedging under price and quantity uncertainty: The case of a cocoa producer. The Journal of Political Economy, 100-116.

Rosen, A. B., Tsai, J. S., & Downs, S. M. (2003). Variations in risk attitude across race, gender, and education. Medical Decision Making, 23(6), 511-517.

Ross, N., Santos, P., & Capon, T. (2010). “Risk, Ambiguity and the Adoption of New Technologies: Experimental Evidence from a Developing Country.” Working paper, University of Sydney.

Rouder, J. N., Lu, J., Speckman, P., Sun, D., & Jiang, Y. (2005). A hierarchical model for estimating response time distributions. Psychonomic Bulletin & Review, 12(2), 195-223.

Roumasset, J. A. (1976). Rice and risk. Decision making among low-income farmers. North Holland Publishing Co. Amsterdam

Runde, J. (1998). Clarifying Frank Knight's discussion of the meaning of risk and uncertainty. Cambridge Journal of Economics, 22(5), 539-546.

Saint-Charles, J., & Mongeau, P. (2009). Different relationships for coping with ambiguity and uncertainty in organizations. Social Networks, 31(1), 33-39.

Sarin, R., & Wakker, P. (1992). A simple axiomatization of nonadditive expected utility. Econometrica: Journal of the Econometric Society, 1255-1272.

Sarin, R., & Wakker, P. (1994). Gains and losses in nonadditive expected utility. In Models and Experiments in Risk and Rationality (pp. 157-172). Springer Netherlands.

Sarin, R., & Wakker, P. P. (2000). Cumulative dominance and probabilistic sophistication. Mathematical Social Sciences, 40(2), 191-196.Schoemaker, P. J. (1993). Determinants of risk-taking: Behavioral and economic views. Journal of Risk and Uncertainty, 6(1), 49-73.

Schrader, S., Riggs, W. M., & Smith, R. P. (1993). Choice over uncertainty and ambiguity in technical problem solving.

Schubert, R., Brown, M., Gysler, M., & Brachinger, H. W. (1999). Financial decision-making: are women really more risk-averse?. The American economic review, 89(2), 381-385.

Semin, G. R., & Manstead, A. S. R. (1983). The accountability of conduct: A social psychological analysis. New York: Academic Press

Sengupta, J. K. (2012). Optimal decisions under uncertainty: methods, models, and management. Springer Science & Business Media.

Senkondo, E. M. (2000). Risk attitude and risk perception in agroforestry decisions: The case of Babati, Tanzania.

Serfilippi, E., Carter, M., & Guirkinger, C. (2015). Certain and uncertain utility and insurance demand: results from a framed field experiment in Burkina Faso. In International Association of Agricultural Economists conference, Milan (pp. 9-14).

Shafir, S. (2000). Risk-sensitive foraging: the effect of relative variability. Oikos, 88(3), 663-669.

Shehu, A., & Abubakar, N. (2015) Determinants of Participation of Farm Households in Non-Farm Enterprise Activities in Rural Nigeria. International Journal of Economics, Commerce and Management 3(6), 57-71.

Shiffrin, R. M., Lee, M. D., Kim, W., & Wagenmakers, E. J. (2008). A survey of model evaluation approaches with a tutorial on hierarchical Bayesian methods. Cognitive Science, 32(8), 1248-1284.

Shleifer, A., Bordalo, P., & Gennaioli, N. (2012). Salience theory of choice under risk. The Quarterly Journal of Economics, 127(3):1243– 1285.

Sillano, M., & de Dios Ortúzar, J. (2005). Willingness-to-pay estimation with mixed logit models: some new evidence. Environment and Planning A, 37(3), 525-550.

Somasundaram, J., & Diecidue, E. (2015). Regret Theory and Risk Attitudes INSEAD Working Paper No. 2015/90/DSC. Available at SSRN: https://ssrn.com/abstract=2691397 or http://dx.doi.org/10.2139/ssrn.2691397

Stigler, G. J., & Becker, G. S. (1977). De gustibus non est disputandum. The American Economic Review, 76-90.

Stone, B. K. (1973). A linear programming formulation of the general portfolio selection problem. Journal of Financial and Quantitative Analysis, 8(4), 621-636.

Stone, E. R., & Allgaier, L. (2008). A social values analysis of self-other differences in decision making involving risk. Basic and Applied Social Psychology, 30,114–129.

Stone, E. R., Yates, A. J., & Caruthers, A. S. (2002). Risk Taking in Decision Making for Others Versus the Self1. Journal of Applied Social Psychology,32(9), 1797-1824.

Stott, Henry P. "Cumulative prospect theory's functional menagerie." Journal of Risk and uncertainty 32, no. 2 (2006): 101-130.

Suleiman, D. E. (2016). Mental health disorders in Nigeria: A highly neglected disease. Annals of Nigerian Medicine, 10(2), 47.

Sulewski, P., & Kłoczko-Gajewska, A. (2014). Farmers' risk perception, risk aversion and strategies to cope with production risk: an empirical study from Poland. Studies in Agricultural Economics, 116(3), 140-147.

Suter, R., Pachur, T., & Hertwig, R. (2013). How Does Prospect Theory Reflect Heuristics' Probability Sensitivity in Risky Choice?. In CogSci.

Sutter, M., Angerer, S., Rützler, D., & Lergetporer, P. (2015). The Effect of Language on Economic Behavior: Experimental Evidence from Children's Intertemporal Choices.

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: linking experimental and household survey data from Vietnam. The American Economic Review, 100(1), 557-571.

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2016). Risk and time preferences: linking experimental and household survey data from Vietnam. In Behavioral Economics of Preferences, Choices, and Happiness (pp. 3-25). Springer Japan.

Tao Yang, D. (1997). Education and off-farm work. Economic development and cultural change, 45(3), 613-632.

Tauer, L. W. (1986). Risk preferences of dairy farmers. North Central Journal of Agricultural Economics, 7-15.

Tavernier, E. M., Temel, T. T., & Li, F. (1997). The role of farm ownership in off-farm work participation. Agricultural and Resource Economics Review, 26, 67-81.

Tetlock, P. E. (1992). The impact of accountability on judgment and choice: Toward a social contingency model. Advances in Experimental Social Psychology, 25, 331-376

Thaler, R. H., Tversky, A., Kahneman, D., & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. The Quarterly Journal of Economics, 647-661.

Tian, L., Huang, H., & Wang, X. (2012). Network Equilibrium Modeling Considering the Travelers' Risk Perception on Arrival Time. In CICTP 2012: Multimodal Transportation Systems—Convenient, Safe, Cost-Effective, Efficient (pp. 457-467).

Tijani, B., Benisheik, K., Mustapha, A., & Dangaladima, W. (2010). Analysis of factors influencing labour supplied to non-farm sub-sector by households in Mubi North local government area of Adamawa state, Nigeria. Nigerian Journal of Basic and Applied Sciences, 18(1), 6-18.

Tobler, P. N., O'Doherty, J. P., Dolan, R. J., & Schultz, W. (2007). Reward value coding distinct from risk attitude-related uncertainty coding in human reward systems. Journal of neurophysiology, 97(2), 1621-1632.

Torkamani, J., & Haji-Rahimi, M. (2010). Evaluation of farmer's risk attitudes using alternative utility functional forms. Journal of Agricultural Science and Technology, 3, 243-248.

Toubia, O., Johnson, E., Evgeniou, T., & Delquié, P. (2013). Dynamic experiments for estimating preferences: An adaptive method of eliciting time and risk parameters. Management Science, 59(3), 613-640.

Train, K. (2001). A comparison of hierarchical Bayes and maximum simulated likelihood for mixed logit. University of California, Berkeley, 1-13.

Train, K., & Sonnier, G. (2005). Mixed logit with bounded distributions of correlated partworths. In Applications of simulation methods in environmental and resource economics (pp. 117-134). Springer Netherlands.

Tremblay, C. H. (2011). Workplace accommodations and job success for persons with bipolar disorder. Work, 40(4), 479-487.

Tremblay, C. H., Grosskopf, S., & Yang, K. (2010). Brainstorm: Occupational choice, bipolar illness and creativity. Economics & Human Biology, 8(2), 233-241.

Tsanakas, A., & Christofides, N. (2006). Risk exchange with distorted probabilities. Astin Bulletin, 36(01), 219-243.

Tsetsos, K., Chater, N., & Usher, M. (2012). Salience driven value integration explains decision biases and preference reversal. Proceedings of the National Academy of Sciences, 109(24), 9659-9664

Tu, Q. (2005). Empirical analysis of time preferences and risk aversion (No. 01bd1b38-5741-4f44-8996-758775fef87e). Tilburg University, School of Economics and Management.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. Cognitive psychology, 5(2), 207-232.

Tymula, A., Glimcher, P. W., Levy, I., & Belmaker, L. A. R. (2012). Separating risk and ambiguity preferences across the life span: Novel findings and implications for policy. Unpublished manuscript.

Ullah, R., Shivakoti, G. P., & Ali, G. (2015). Factors effecting farmers' risk attitude and risk perceptions: the case of Khyber Pakhtunkhwa, Pakistan. International journal of disaster risk reduction, 13, 151-157.

Van De Kuilen, G., & Wakker, P. P. (2011). The midweight method to measure attitudes toward risk and ambiguity. Management Science, 57(3), 582-598.

VanWey, L., & Vithayathil, T. (2013). Off-farm work among rural households: a case study in the Brazilian Amazon. Rural sociology, 78(1), 29-50.

van Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., & Wauters, E. (2014). Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies. Journal of Risk Research, (ahead-of-print), 1-23.

van Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., & Wauters, E. (2016). Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies. Journal of Risk Research, 19(1), 56-78.

Vargas Hill, R. (2009). Using stated preferences and beliefs to identify the impact of risk on poor households. The Journal of Development Studies, 45(2), 151-171.

Vieider, F. M. (2009). The effect of accountability on loss aversion. Acta psychologica, 132(1), 96-101.

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2014). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. Journal of the European Economic Association.

Vieider, F. M., Truong, N., Martinsson, P., & Nam, P. K. (2013). Risk preferences and development revisited: A field experiment in Vietnam (No. SP II 2013-403). WZB Discussion Paper.

Vieider, F. M., Villegas-Palacio, C., Martinsson, P., & Mejía, M. (2016). Risk taking for oneself and others: A structural model approach. Economic Inquiry, 54(2), 879-894.

Vos, T., Barber, RM., Bell, B., Bertozzi-Villa, A., Biryukov, S., Bolliger, I., …Murray, CJ.. (2013). Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries, 1990–2013: A systematic analysis for the Global Burden of Disease study. The Lancet, 386(9995), 743–800.

Wakker, P. (1990). Under stochastic dominance Choquet-expected utility and anticipated utility are identical. Theory and Decision, 29(2), 119-132.

Wakker, P. (2001). ‘‘Testing and Characterizing Properties of Nonadditive Measuresthrough Violations of the Sure-Thing Principle’’. Econometrica 69, 1039-1059.

Wakker, Peter P. and Amos Tversky (1993). “An Axiomatization of Cumulative Prospect Theory.” Journal of Risk and Uncertainty, 7:7:147-176.

Wang, L. L., & Wang, R. Z. (2012). Impact of Risk Aversion on Optimal Decisions in Supply Contracts with Bidirectional Options. In Applied Mechanics and Materials (Vol. 235, pp. 261-266).

Warshawsky-Livne, L., A'wad, F., Shkolnik-Inbar, J., & Pliskin, J. S. (2012). A note on the relationship between health-risk attitude and monetary-risk attitude.Health, Risk & Society, 14(4), 377-383.

Ward, P. S., & Singh, V. (2014). Risk and ambiguity preferences and the adoption of new agricultural technologies: Evidence from field experiments in rural India (Vol. 1324). Intl Food Policy Res Inst.

Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. Journal of behavioral decision making, 15, 263-290

Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. Journal of behavioral decision making, 15(4), 263-290.

Weber, E. U., Shafir, S., & Blais, A. R. (2004). Predicting risk sensitivity in humans and lower animals: risk as variance or coefficient of variation. Psychological review, 111(2), 430.

Weigold, M. F., & Schlenker, B. R. (1991). Accountability and Risk Taking. Personality and Social Psychology Bulletin 17, 25-29.

Weissman, M. M., Bruce, M. L., Leaf, P. J., Florio, L. P., & Holzer, C. (1991). Affective disorders. Psychiatric disorders in America, The Epidemiologic Catchment Area Study. New York, Free Press, 53-80.

Welch, B. L. (1947). "The generalization of "Student's" problem when several different population variances are involved". Biometrika. 34 (1–2): 28–35.

WHO (2009). ECOSOC Meeting “Addressing non-communicable diseases and mental health: major challenges to sustainable development in the 21st century” Discussion Paper "Mental health, poverty and development", July 2009. Retrived from http://www.who.int/nmh/publications/discussion_paper_en.pdf

Wik, M., Aragie Kebede, T., Bergland, O., & Holden, S. T. (2004). On the measurement of risk aversion from experimental data. Applied Economics, 36(21), 2443-2451.

Wilcox, N. T. (2015). Unusual estimates of probability weighting functions. ESI Working Paper 15-10. Retrieved from http://digitalcommons.chapman.edu/esi_working_papers/159

Wilde, J. (2000). Identifcation of multiple probit models with endogenous dummy regressors.

Wilson, P. N., & Eidman, V. R. (1983). An empirical test of the interval approach for estimating risk preferences. Western Journal of Agricultural Economics, 170-182.

Wossen, T., Berger, T., & Di Falco, S. (2015). Social capital, risk preference and adoption of improved farm land management practices in Ethiopia.Agricultural Economics, 46(1), 81-97.

Wright, W. F., & Bower, G. H. (1992). Mood effects on subjective probability assessment. Organizational behavior and human decision processes, 52(2), 276-291.

Xavier G, Corinne F, Schleich J & Meissner (2017). "Determinant of risk and time preferences - A multi-countries experiment." - submitted to ESA (Experimental Science Association), Californie, San Diego, 2017 and to ASFEE (Association Française d'Economie Expérimentale) 2017, Rennes, France.

Xu, P., Alexander, C., Patrick, G., & Musser, W. (2005). Effects of Farmers' Risk Attitudes and Personality Types on Production and Marketing Decisions. Staff Paper, (05-10).

Yechiam, E., Hayden, E. P., Bodkins, M., O'Donnell, B. F., & Hetrick, W. P. (2008). Decision making in bipolar disorder: a cognitive modeling approach. Psychiatry research, 161(2), 142-152.

Yesuf, M., & Bluffstone, R. (2007). Risk Aversion in Low Income Countries. Working Paper, IFPRI.

Yesuf, Mahmud, and Randall A. Bluffstone (2009) 'Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from ethiopia.' American Journal of Agricultural Economics 91(4), 1022–1037

Zahonogo, P. (2011). Determinants of non-farm activities participation decisions of farm households in Burkina Faso. Journal of Development and Agricultural Economics, 3(3), 174-182.

Zakamouline, V., & Koekebakker, S. (2009). A Generalisation of the Mean-Variance Analysis. European Financial Management, 15(5), 934-970.

Zeelenberg, M., & Pieters, R. (2007). A theory of regret regulation 1.0. Journal of Consumer psychology, 17(1), 3-18.

Zeelenberg, M., Beattie, J., Van der Pligt, J., & de Vries, N. K. (1996). Consequences of regret aversion: Effects of expected feedback on risky decision making. Organizational behavior and human decision processes, 65(2), 148-158.

Zeelenberg, M., Van Dijk, W. W., SR Manstead, A., & der Pligt, J. (1998). The experience of regret and disappointment. Cognition & Emotion, 12(2), 221-230.

ZgaJnar, J., & Kavcic, S. (2011). Indirect estimation of farm's risk aversion: mathematical programming approach. Bulgarian Journal of Agricultural Science, 17(2), 218-231.

Zhang, X., Liu, Y., Chen, X., Shang, X., & Liu, Y. (2017). Decisions for Others Are Less Risk-Averse in the Gain Frame and Less Risk-Seeking in the Loss Frame Than Decisions for the Self. Frontiers in psychology, 8, 1601.

Zhou, F., Ji, Y., & Jiao, R. J. (2014). Prospect-theoretic modeling of customer affective-cognitive decisions under uncertainty for user experience design. IEEE Transactions on Human-Machine Systems, 44(4), 468-483.

Zimmerman, L., Shalvi, S., and Bereby-Meyer, Y. (2014). Self-reported ethical risk taking tendencies predict actual dishonesty. Judgm. Decis. Mak. 9, 58–64

Zimper, A. (2009). Half empty, half full and why we can agree to disagree forever. Journal of Economic Behavior & Organization, 71(2), 283-299.

Appendix

Appendix 1: Definition of variables

Variable	Description
AGE	Age in Years
GENDER	1 = Male, 0 = otherwise
M.STATUS	Married = 1, 0 = otherwise
L.EDU	No formal Education = Reference
	Primary School = 1, 0 = otherwise
	Secondary School = 1, 0 = otherwise
	Higher Education = 1, 0 = otherwise
H.H SIZE	Number of Persons
P.OCC.TYPE	Farmer = 1, 0 = otherwise
OWNER.P	Own business = 1, 0 = otherwise
N.YEARS.P	Number of years in primary occupation
TIME.SPENT	Hours spent per day in primary occupation
SEC.OCCU	Yes = 1, 0 = otherwise
SEC.OCCU.TYPE	Crop Farmer = 1, 0 = otherwise
OWNER.S	Own business = 1, 0 = otherwise
N.YEARS.S	Number of years in secondary occupation
TIME.SP.SEC	Hours spent per day in secondary occupation
FARM.SIZE	Farm size in hectare(s)
OFIGA	1 = participate in off-farm income gen. activities, 0 = otherwise
BPDt	1 = Bipolar tendencies, 0 = otherwise

Appendix 2: Participant level curvature of the subjective value and probability weighting functions

	Risk				Uncertainty			
ID	α	β	γ^{+}	γ^{-}	α	β	γ^{+}	γ^{-}
1	X	X	S	IS	X	X	S	IS
2	C	C	IS	S	C	C	IS	S
3	X	X	S	IS	X	X	S	IS
4	X	X	S	IS	X	X	S	IS
5	C	X	IS	IS	C	X	IS	IS
6	C	C	S	IS	C	C	S	IS
7	X	X	S	IS	X	X	S	IS
8	C	C	IS	IS	C	C	IS	IS
9	C	X	IS	S	C	C	IS	S
10	C	X	IS	S	C	X	IS	S
11	C	X	IS	IS	C	X	IS	IS
12	C	C	IS	IS	C	C	IS	IS
13	X	X	S	IS	C	X	S	IS
14	X	C	S	S	X	X	S	S
15	C	X	IS	S	C	X	IS	S
16	X	C	S	S	C	X	S	S
17	X	C	S	S	X	C	S	S
18	X	X	S	IS	C	C	S	IS
19	X	X	IS	S	C	X	IS	S
20	X	C	S	S	X	C	S	S
21	X	X	S	IS	X	C	S	IS
22	C	C	IS	IS	C	C	IS	IS
23	C	C	IS	S	C	C	IS	S
24	C	C	IS	IS	C	C	IS	IS
25	C	C	IS	S	C	C	IS	S
26	C	X	IS	IS	C	X	IS	IS
27	C	X	S	IS	X	C	S	IS
28	X	C	S	S	X	C	S	S
29	C	X	IS	IS	X	X	IS	IS
30	C	C	IS	S	C	C	IS	S
31	X	C	S	IS	C	X	S	IS
32	C	X	IS	IS	C	X	IS	IS
33	C	C	S	IS	C	X	S	IS
34	C	C	S	IS	X	X	S	IS
35	C	X	IS	S	C	C	IS	S
36	C	X	IS	IS	C	X	IS	IS
37	C	X	S	IS	C	X	S	IS
38	C	C	IS	IS	X	C	IS	IS
39	X	C	S	S	X	X	S	S
40	C	C	IS	IS	C	C	IS	IS
41	C	C	S	S	C	X	S	S

42	X	X	S	IS	X	X	S	IS
43	C	X	IS	IS	C	C	IS	IS
44	X	X	S	IS	C	X	S	IS
45	C	C	IS	IS	C	X	IS	IS
46	X	X	S	S	X	X	S	S
47	C	X	IS	IS	C	X	IS	IS
48	X	X	S	IS	X	X	S	IS
49	C	X	IS	IS	C	C	IS	IS
50	C	X	IS	IS	X	X	IS	IS
51	C	X	IS	IS	X	C	IS	IS
52	X	X	S	IS	C	X	S	IS
53	C	X	IS	IS	C	C	IS	IS
54	X	X	S	IS	X	X	S	IS
55	C	X	IS	IS	X	C	IS	IS
56	C	X	IS	IS	C	C	IS	IS
57	X	C	S	S	C	C	S	S
58	X	X	IS	IS	C	X	IS	IS
59	C	X	IS	IS	X	X	IS	IS
60	C	C	IS	S	X	X	IS	S
61	X	X	IS	IS	C	X	IS	IS
62	C	C	IS	IS	C	C	IS	IS
63	C	C	IS	IS	C	X	IS	IS
64	C	C	IS	IS	C	X	IS	IS
65	C	X	IS	S	X	C	IS	S
66	C	X	IS	S	X	C	IS	S
67	X	X	S	IS	C	X	S	IS
68	C	C	IS	IS	C	C	IS	IS
69	C	C	IS	S	C	C	IS	S
70	C	X	IS	IS	C	X	IS	IS
71	C	C	S	IS	X	X	S	IS
72	X	X	IS	IS	X	X	IS	IS
73	C	C	IS	IS	C	C	IS	IS
74	C	X	S	IS	C	X	S	IS
75	C	X	IS	S	C	C	IS	S
76	X	C	S	S	X	C	S	S
77	C	X	S	IS	C	X	S	IS
78	C	X	IS	IS	C	X	IS	IS
79	X	C	S	S	X	C	S	S
80	C	X	S	IS	C	X	S	IS
81	C	C	IS	S	C	C	IS	S
82	C	X	IS	IS	C	X	IS	IS
83	X	X	S	IS	X	X	S	IS
84	C	C	IS	IS	C	C	IS	IS
85	X	X	S	IS	X	X	S	IS
86	X	X	S	IS	X	X	S	IS
87	C	C	IS	S	C	C	IS	S

88	X	C	S	S	X	C	S	S
89	C	C	IS	S	C	C	IS	S
90	C	X	IS	IS	C	X	IS	IS
91	C	X	IS	IS	C	C	IS	IS
92	C	X	IS	IS	C	X	IS	IS
93	C	X	IS	IS	C	X	IS	IS
94	C	C	IS	S	C	C	IS	S
95	C	X	IS	IS	C	X	IS	IS
96	C	C	IS	IS	X	C	IS	IS
97	C	C	IS	S	C	C	IS	S
98	C	C	IS	IS	C	C	IS	IS
99	C	X	IS	IS	C	X	IS	IS
100	C	X	IS	IS	C	X	IS	IS
101	C	X	IS	IS	C	X	IS	IS
102	C	C	IS	IS	C	C	IS	IS
103	C	X	S	IS	C	X	S	IS
104	C	X	IS	IS	C	C	IS	IS
105	C	C	IS	S	C	X	IS	S
106	C	C	IS	IS	C	C	IS	IS
107	C	X	IS	IS	C	X	IS	IS
108	C	C	S	S	X	X	S	S
109	C	X	IS	IS	C	X	IS	IS
110	X	X	S	S	X	X	S	S
111	X	X	IS	S	C	X	IS	S
112	X	X	S	IS	X	X	S	IS
113	C	X	IS	S	C	C	IS	S
114	C	C	IS	IS	C	X	IS	IS
115	C	X	IS	IS	C	X	IS	IS
116	C	C	S	S	X	C	S	S
117	C	X	IS	IS	C	C	IS	IS
118	C	C	IS	IS	C	C	IS	IS
119	X	X	S	IS	X	X	S	IS
120	C	C	S	S	C	X	S	S
121	C	X	IS	IS	C	C	IS	IS
122	X	X	S	S	C	X	S	S
123	C	X	IS	IS	X	C	IS	IS
124	C	C	IS	S	C	C	IS	S
125	C	X	S	IS	C	X	S	IS
126	X	C	S	S	X	X	S	S
127	C	C	S	IS	C	X	S	IS
128	C	X	IS	IS	C	C	IS	IS
129	X	X	IS	IS	C	C	IS	IS
130	C	C	IS	IS	X	C	IS	IS
131	X	X	IS	IS	C	X	IS	IS
132	C	C	IS	S	C	C	IS	S
133	C	X	IS	IS	C	X	IS	IS

134	C	C	IS	S	C	C	IS	S
135	C	C	IS	IS	C	C	IS	IS
136	C	X	IS	IS	C	X	IS	IS
137	C	X	IS	IS	C	X	IS	IS
138	X	X	S	IS	X	X	S	IS
139	C	X	IS	IS	C	X	IS	IS
140	C	X	IS	IS	C	C	IS	IS
141	C	C	IS	IS	C	X	IS	IS
142	C	C	IS	S	C	C	IS	S
143	C	C	IS	IS	C	C	IS	IS
144	C	C	S	IS	X	C	S	IS
145	C	C	IS	S	C	C	IS	S
146	C	C	IS	IS	C	C	IS	IS
147	C	X	IS	S	C	X	IS	S
148	C	X	IS	IS	C	X	IS	IS
149	X	X	IS	IS	C	X	IS	IS
150	C	C	IS	IS	C	C	IS	IS
151	C	C	IS	IS	C	C	IS	IS
152	C	C	IS	IS	C	C	IS	IS
153	C	C	IS	IS	C	C	IS	IS
154	C	X	IS	IS	C	C	IS	IS
155	X	X	S	IS	C	C	S	IS
156	C	X	IS	S	X	X	IS	S
157	X	C	S	IS	C	C	S	IS
158	C	C	IS	IS	C	C	IS	IS

Key: C=Concave, X= Convex, IS=Inverse-S shape, S = S-shape

Appendix 3: Questionnaire

HOUSEHOLD ID: …………………………………….. DATE:…………………

STATE………………………………

COMMUNITY/VILLAGE………………………………………

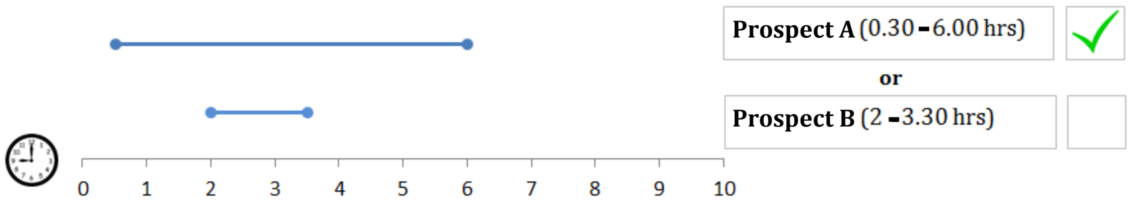
Interview is administered to the household head ( ) 1

Interview is administered to a close family member ( ) 2 *

* Relationship with household head……………………………………………..

Example: Section A

Here is an example of a farmer who was faced with two choice situations regarding time taken to get vaccinated.



The farmer was informed that two NGO's were running new health centres in his Local Government Area with facilities on opposite wings in the same building however with same level of service provision. Generally, there was a processing (registration) time between arrival and when the vaccine was administered. The malaria vaccine was available for free for a limited number of days and he was expected to arrive at 9am if he decides to attend one of the clinic sessions.

The processing time for the first NGO presented as prospect A will take 30 minutes (*i.e.* it will take 30 minutes to complete his registration) after which he will be *equally likely* to be called in for the vaccine at any time between 30 minutes and 6 hours. While for the second NGO presented as prospect B, the registration time will take 2 hours after which he will be *equally likely* to be called in for the vaccine at any time between 2 hours and 3 hours 30 minutes. Given that he had to make a choice between prospects A or B,

The farmer chose Prospect A.

That means he choose the prospect where it was equally likely to take him any-time 54 minutes and 8 hours 36 minutes to get to vaccinated.

In the section that follows, you will be asked similar questions and will be expected to provide you own genuine answer.

A.

Two NGO's are running new health centres in the Local Government Area with facilities on opposite wings in the same building however with same level of service. Generally, there is a processing (registration) time between arrival and when the vaccine will be administered. At the moment, this malaria vaccine will be available for free for a limited number of days and you are expected to arrive at 9am if you decide to attend one of the clinic sessions.

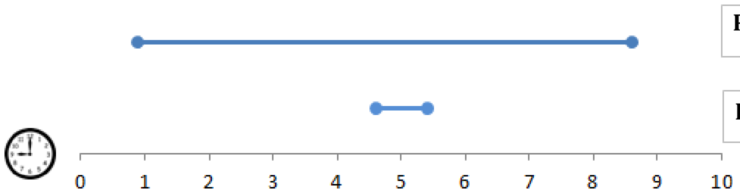
In Question 1 (presented below) the processing time for the first NGO with prospect A will take 54 minutes (i.e. it will take 54 minutes to complete your registration) after which you are *equally likely* to be called in for the vaccine at any time between 54 minutes and 8 hours 36 minutes.

While for the second NGO with prospect B the registration time will take 4 hours 36 minutes after which you are *equally likely* to be called in for the vaccine at any time between 4 hours 36 minutes and 5 hours 24 minutes. Given that you have to make a choice between prospects A or B which one of the two will you choose?

Note

Provide your answer by ticking the box beside your preferred prospect.

1.

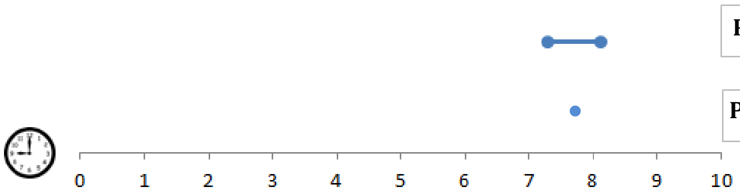


Prospect A (0.54 – 8.36 hrs) ☐

or

Prospect B (4.36 – 5.24hrs) ☐

2.

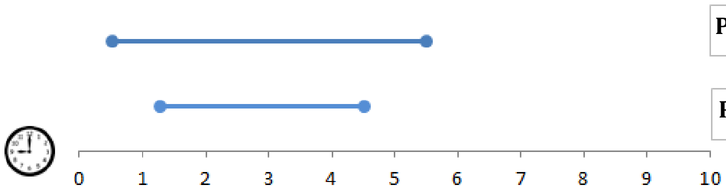


Prospect A (7.18–8.06 hrs) ☐

or

Prospect B (7.42– 7.42hrs) ☐

3.

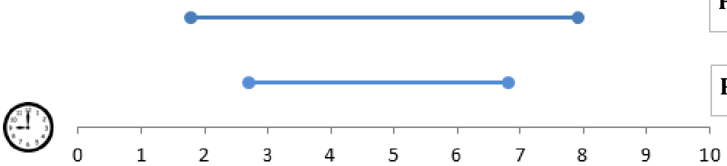


Prospect A (0.30 – 5.30hrs) ☐

or

Prospect B (1.18 – 4.30hrs) ☐

4.

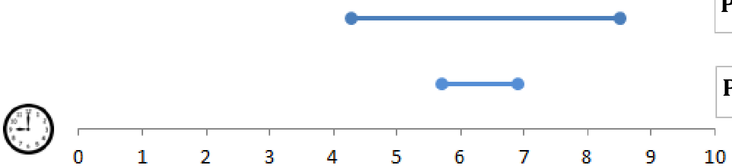


Prospect A (1.48 – 7.54hrs) ☐

or

Prospect B (2.42 – 6.48hrs) ☐

5.

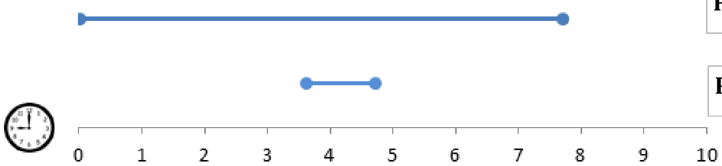


Prospect A (4.18 – 8.30hrs) ☐

or

Prospect B (5.42 – 6.54hrs) ☐

6.

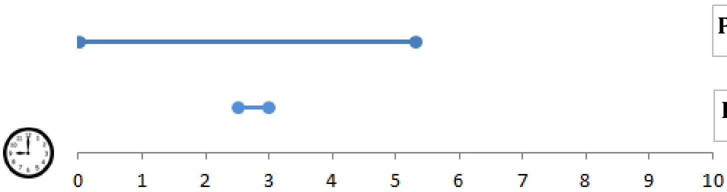


Prospect A (0 – 7.42hrs) ☐

or

Prospect B (3.36 – 4.42hrs) ☐

7.

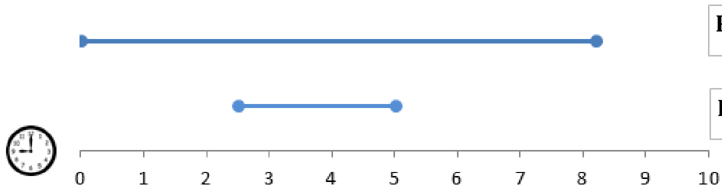


Prospect A (0– 5.18hrs)

or

Prospect B (2.30– 3.00hrs)

8.

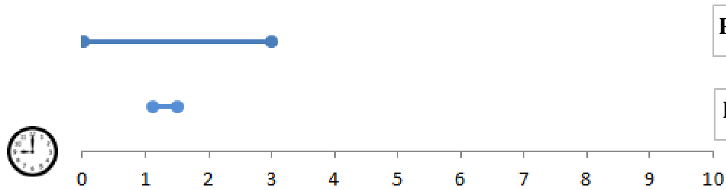


Prospect A (0 – 8.12hrs)

or

Prospect B (2.30 – 5.00hrs)

9.

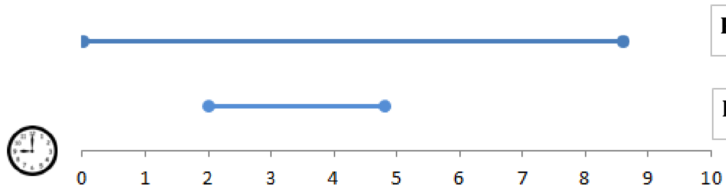


Prospect A (0 – 3.00hrs)

or

Prospect B (1.06 – 1.30hrs)

10.



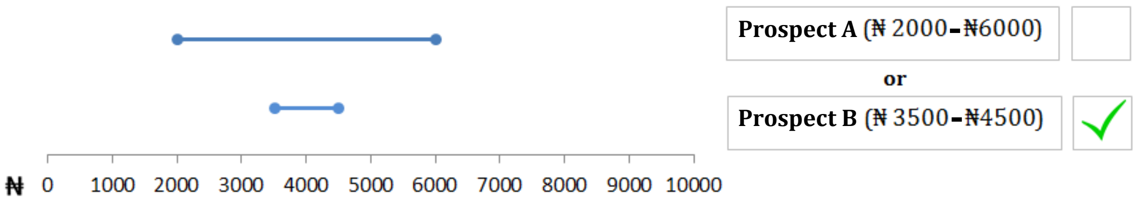
Prospect A (0 – 8.36hrs)

or

Prospect B (2 – 4.48hrs)

Example: Section B

Here is an example of a farmer who was presented with a set of monetary prospects as shown below.



For Prospect A, he was *equally likely* to earn any amount between ₦2000 and ₦6000. For Prospect B he was *equally likely* to earn any amount between ₦3500 and ₦4500.

The farmers chose Prospect B.

Thus, the farmer was *equally likely* to earn any amount between ₦3500 and ₦4500.

In the section that follows, you will be asked similar questions and will be expected to provide you own genuine answer.

B.

Imagine you are faced with a similar set of monetary prospects as presented below.

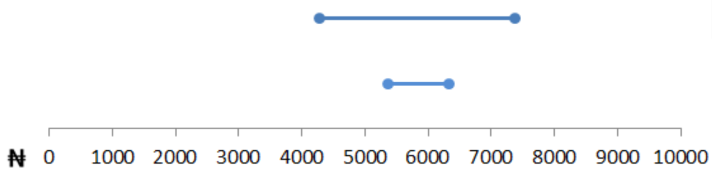
In question 1, you are *equally likely* to earn any amount between ₦4280 and ₦7358 if you choose Prospect A. While you are *equally likely* to earn any amount between ₦5361 and ₦6315 if you choose Prospect B.

Given that you have to make a choice between prospects A or B which one of the two will you choose?

Note

Provide your answer by ticking the box beside your preferred prospect.

1.

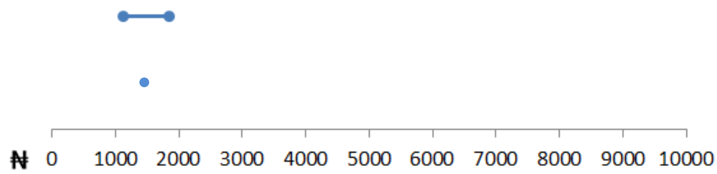


Prospect A (₦4280–₦7358) ☐

or

Prospect B (₦5361–₦6315) ☐

2.

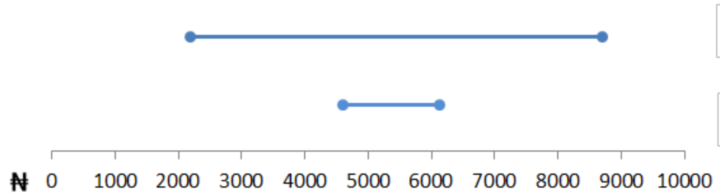


Prospect A (₦1110–₦1836) ☐

or

Prospect B (₦1467–₦1483) ☐

3.

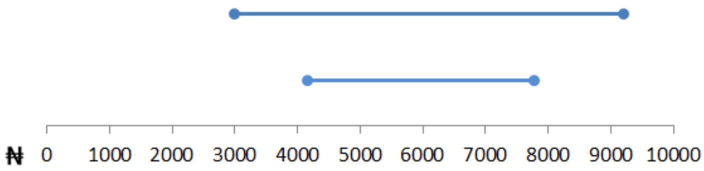


Prospect A (₦2171–₦8694) ☐

or

Prospect B (₦4587–₦6125) ☐

4.

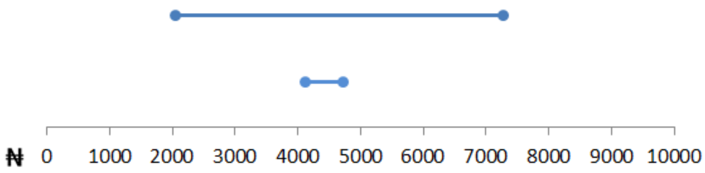


Prospect A (₦2984–₦9199) ☐

or

Prospect B (₦4148–₦7777) ☐

5.

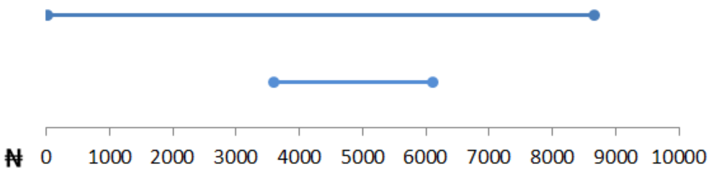


Prospect A (₦2043–₦7272) ☐

or

Prospect B (₦4118–₦4720) ☐

6.

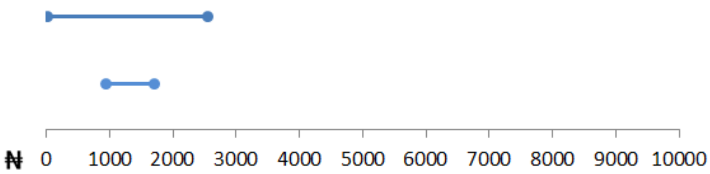


Prospect A (₦0–₦8662) ☐

or

Prospect B (₦3579–₦6108) ☐

7.

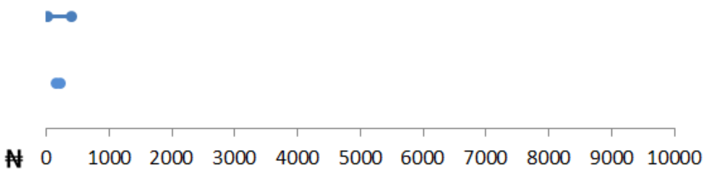


Prospect A (₦0–₦2548) ☐

or

Prospect B (₦926–₦1704) ☐

8.

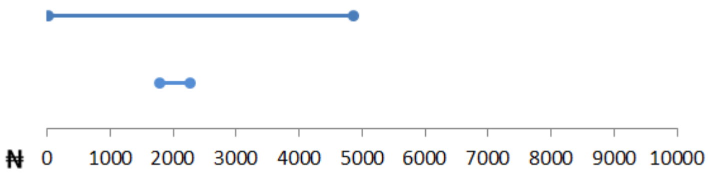


Prospect A (₦0–₦391) ☐

or

Prospect B (₦144–₦217) ☐

9.

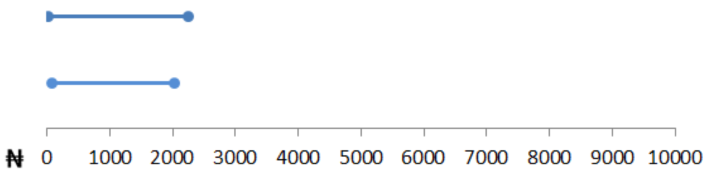


Prospect A (₦0 – ₦4858)

or

Prospect B (₦1777– ₦2264)

10.

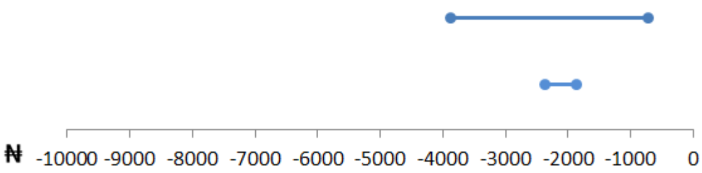


Prospect A (₦0– ₦2246)

or

Prospect B (₦72– ₦2014)

11.

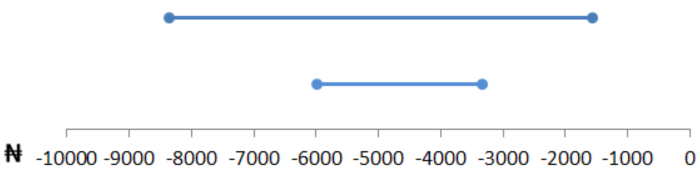


Prospect A (₦-3894– ₦-723)

or

Prospect B (₦-2383 – ₦-871)

12.

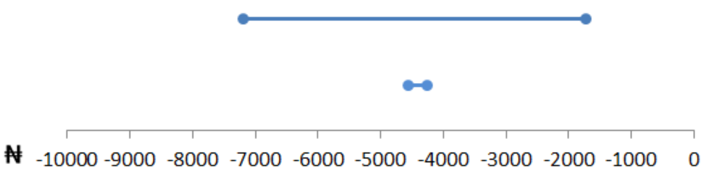


Prospect A (₦-8362– ₦-1578)

or

Prospect B (₦-6005– ₦-3352)

13.

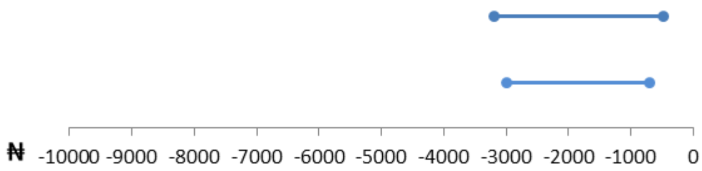


Prospect A (₦-7210– ₦-1739)

or

Prospect B (₦-4565– ₦-4266)

14.

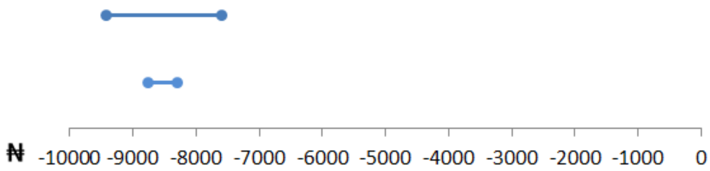


Prospect A (₦-3202– ₦-481)

or

Prospect B (₦-2996 – ₦-710)

15.

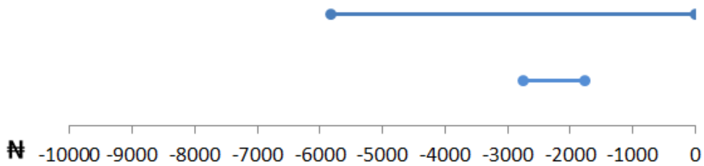


Prospect A (₦-9438– ₦-7604)

or

Prospect B (₦-8764– ₦-8300)

16.

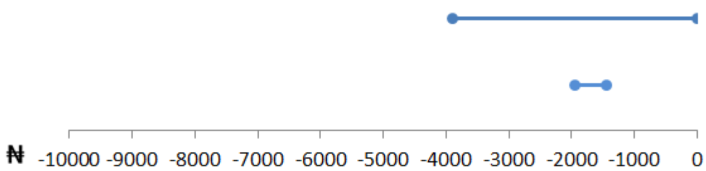


Prospect A (₦-5840 – ₦0)

or

Prospect B (₦-2764 – ₦-1777)

17.

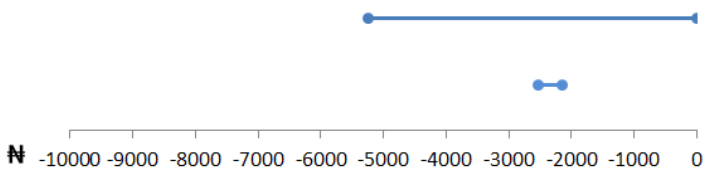


Prospect A (₦-3916– ₦0)

or

Prospect B (₦-1965– ₦-1448)

18.

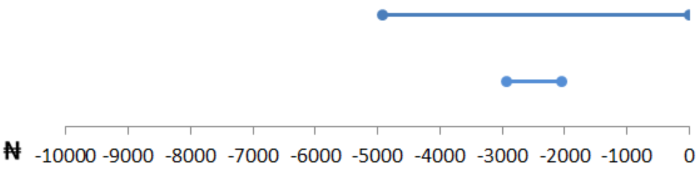


Prospect A (₦-5255– ₦0)

or

Prospect B (₦-2532– ₦-2148)

19.

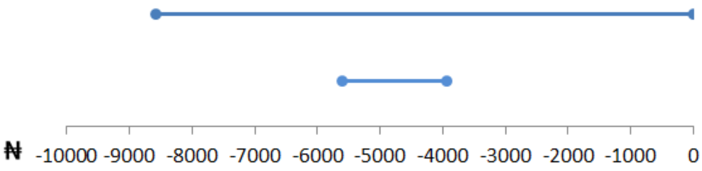


Prospect A (₦-4932–₦0) ☐

or

Prospect B (₦-2936–₦-2065) ☐

20.

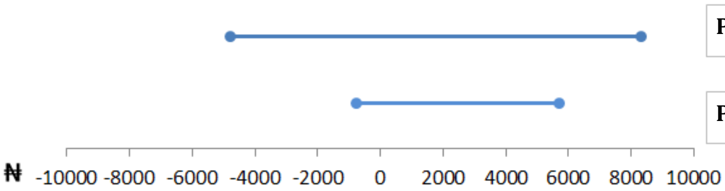


Prospect A (₦-8585–₦0) ☐

or

Prospect B (₦-5624–₦-3947) ☐

21.

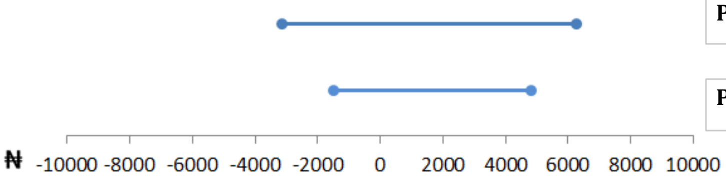


Prospect A (₦-4798–₦8314) ☐

or

Prospect B (₦-803–₦5696) ☐

22.

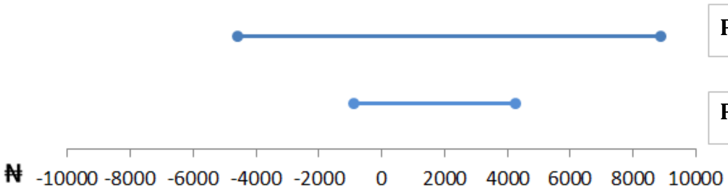


Prospect A (₦-3141–₦6231) ☐

or

Prospect B (₦-1529–₦4817) ☐

23.

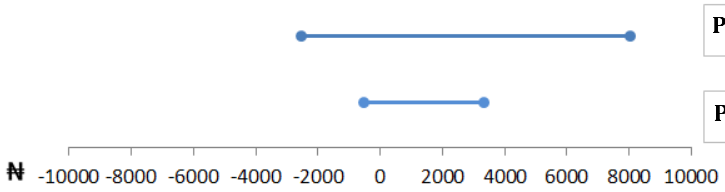


Prospect A (₦-4599–₦8863) ☐

or

Prospect B (₦-924–₦4256) ☐

24.

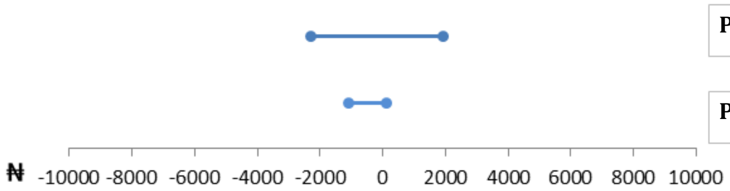


Prospect A (₦-2557–₦8012)

or

Prospect B (₦-535–₦3310)

25.

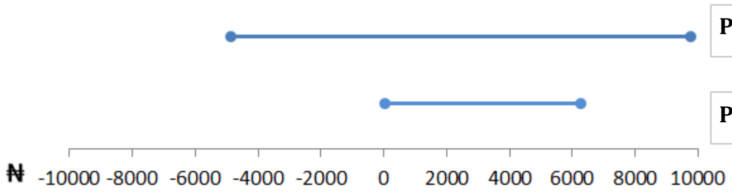


Prospect A (₦-2299–₦1907)

or

Prospect B (₦-1093–₦106)

26.

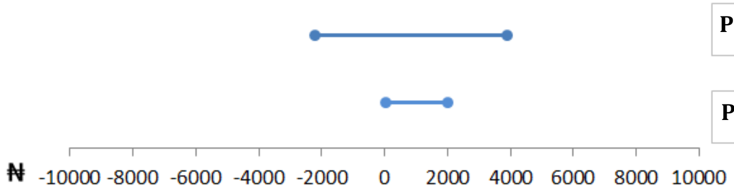


Prospect A (₦-4871–₦9741)

or

Prospect B (₦0–₦6234)

27.

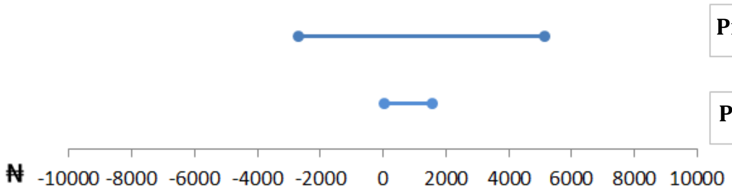


Prospect A (₦-2246–₦3879)

or

Prospect B (₦0–₦1976)

28.

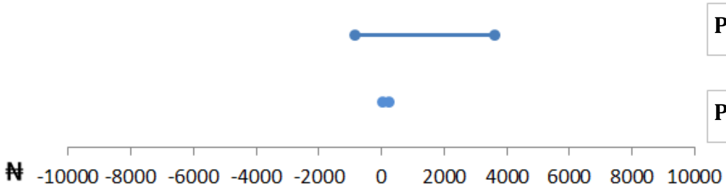


Prospect A (₦-2702–₦5117)

or

Prospect B (₦0–₦1539)

29.

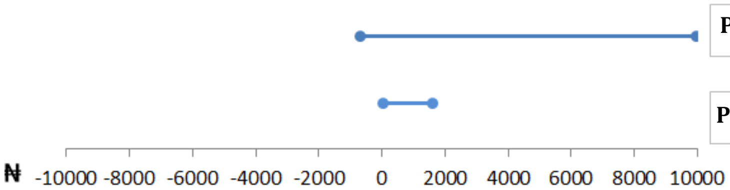


Prospect A (₦-857– ₦3613)

or

Prospect B (₦0– ₦203)

30.

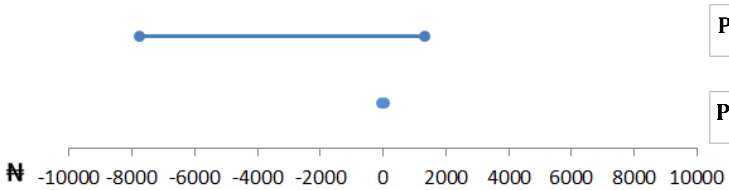


Prospect A (₦-700–₦9956)

or

Prospect B (₦0–₦1569)

31.

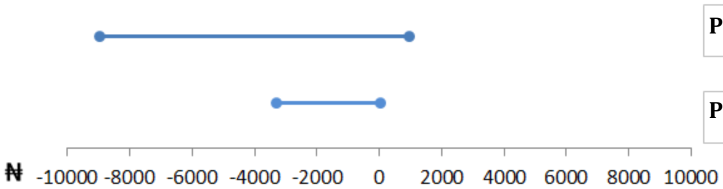


Prospect A (₦-7795–₦1288)

or

Prospect B (₦-67–₦0)

32.

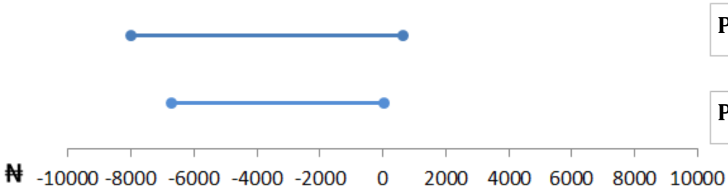


Prospect A (₦-9002–₦940)

or

Prospect B (₦-3335– ₦0)

33.

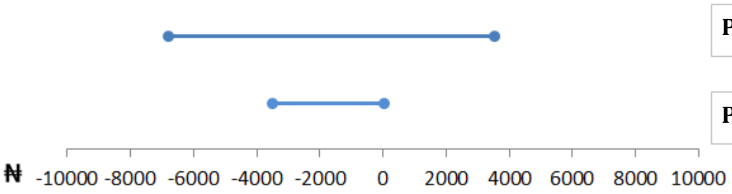


Prospect A (₦-8012–₦602)

or

Prospect B (₦-6731–₦0)

34.

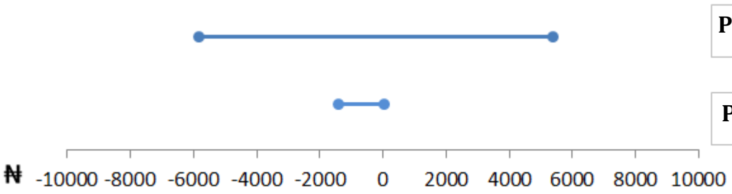


Prospect A (₦-6825–₦3516)

or

Prospect B (₦-3536–₦0)

35.



Prospect A (₦-5856– ₦5376)

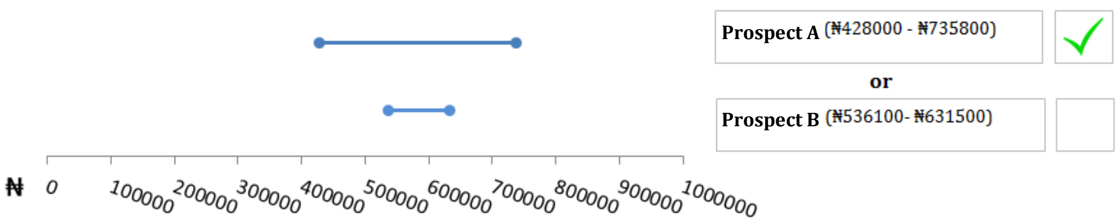
or

Prospect B (₦-1442–₦0)

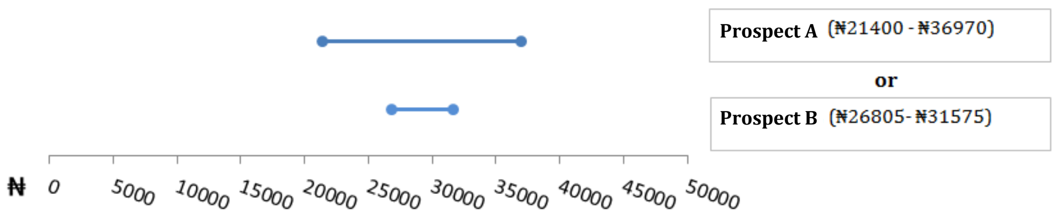
Example: Section C

Here is an example of a farmer who is employed by an agricultural firm as a farm manager with the responsibility of taking decision on this large farm. He reached an agreement with his employer over returns from his decisions - that for any decision taken he will get 5% of the total payoff.

Amount to Firm



Amount to you



In this case for Prospect A, the firm was *equally likely* to earn any amount between ₦428000 and ₦7358000. This implies that the farmer's 5% was *equally likely* to be any amount between ₦21400 and ₦36970 if he chooses Prospect A. While for Prospect B the firm was *equally likely* to earn any amount between ₦536100 and ₦631500. This implies that the farmer's 5% was *equally likely* to be any amount between ₦26805 and ₦31575 if he chooses Prospect B.

The farmers chose Prospect A.

Thus the firm was equally likely to earn any amount between ₦428000 and ₦7358000 while the farmer was equally likely get any amount between ₦21400 and ₦36970.

In the section that follows, you will be asked similar questions and will be expected to provide you own genuine answer.

C.

Suppose that you are employed by an agricultural firm as a farm manager and you have the responsibility of taking decision on this large farm. Currently you are faced with the following situations.

In prospect A, overall the firm is **equally likely** to earn any amount between ₦636146 and ₦858691; and the 5% that accrue to you if you choose prospect A is **equally likely** to be any amount between ₦31807.3 and ₦42934.55.

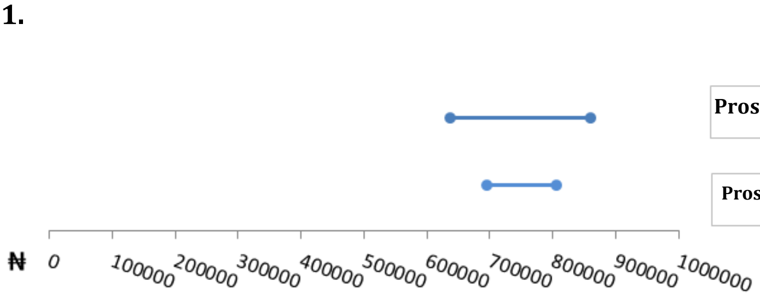
While for prospect B overall the firm is **equally likely** to earn any amount between ₦694532 and ₦804389; and the 5% that accrue to you if you choose prospect B is **equally likely** to be any amount between ₦34726.6 and ₦40219.45

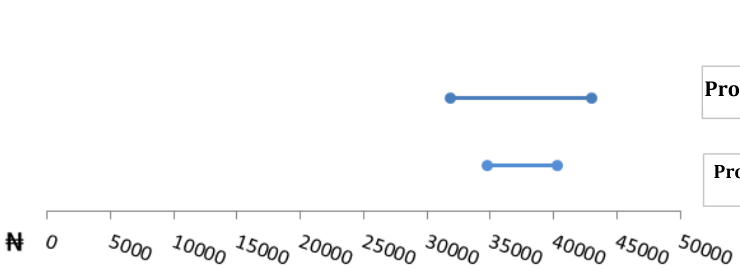
Given that you have to make a choice between either prospects, which of the prospects will you choose?

Note: The pair of prospect from which you are to make the decision on behalf of the firm is the top graph named "Amount to firm". The bottom graph directly below named "Amount to you" is a representation of the 5% you are equally likely to earn from the decision you make as a manager in the firm.

Provide your answer by ticking the box beside your preferred prospect.

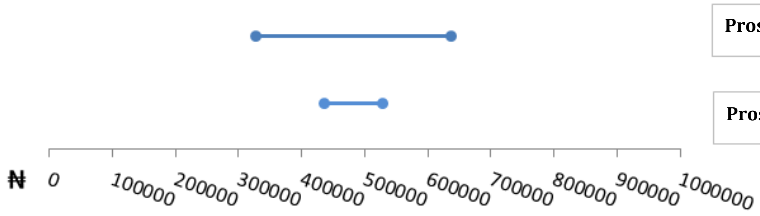
1.





2.

Amount to Firm

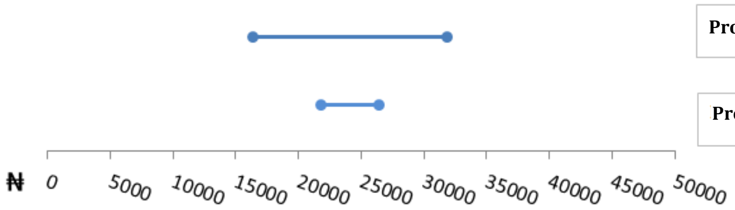


Prospect A (₦326466 - ₦636030)

or

Prospect B (₦435840 - ₦527383)

Amount to you



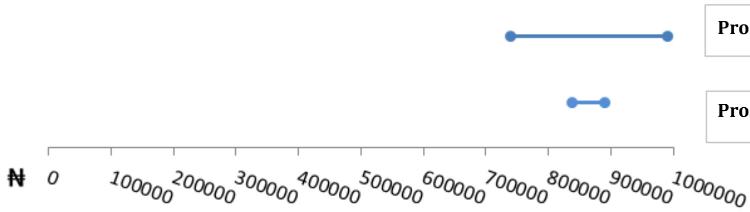
Prospect A (₦16323.3 - ₦31801.5)

or

Prospect B (₦21792 - ₦26369.15)

3.

Amount to Firm

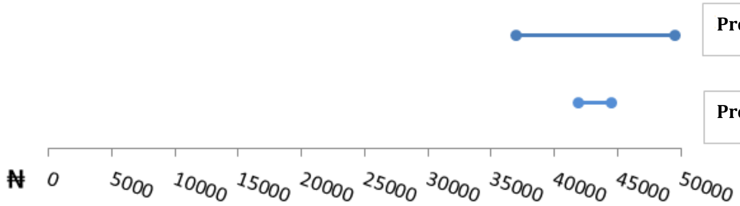


Prospect A (₦739553 - ₦989220)

or

Prospect B (₦837614 - ₦888546)

Amount to you



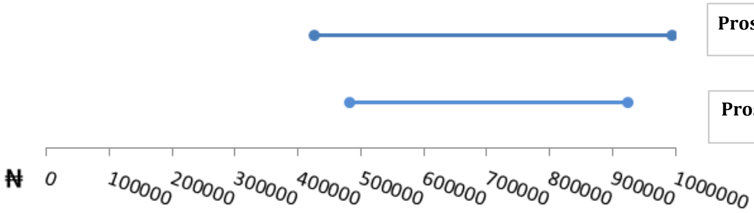
Prospect A (₦36977.65 - ₦49461)

or

Prospect B (₦41880.7 - ₦44427.3)

4.

Amount to Firm

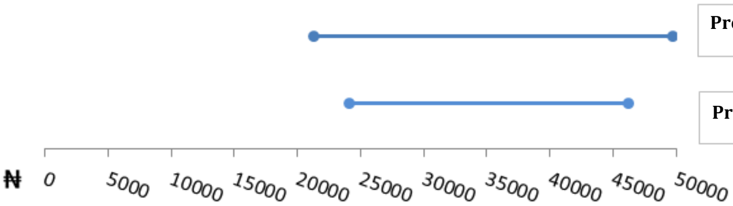


Prospect A (₦424252 - ₦994234)

or

Prospect B (₦481335 - ₦924514)

Amount to you



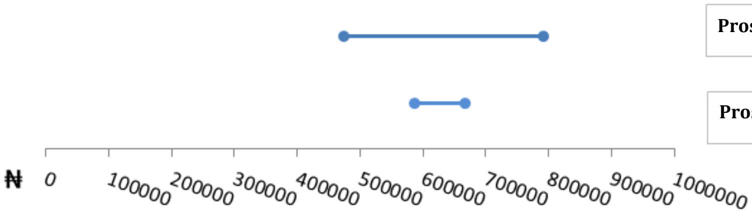
Prospect A (₦21212.6 - ₦49711.7)

or

Prospect B (₦24066.75 - ₦46225.7)

5.

Amount to Firm

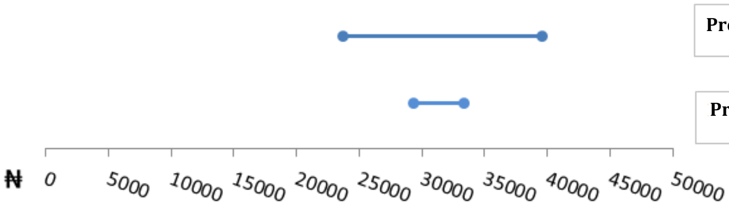


Prospect A (₦472473 - ₦790866)

or

Prospect B (₦585818 - ₦665648)

Amount to you



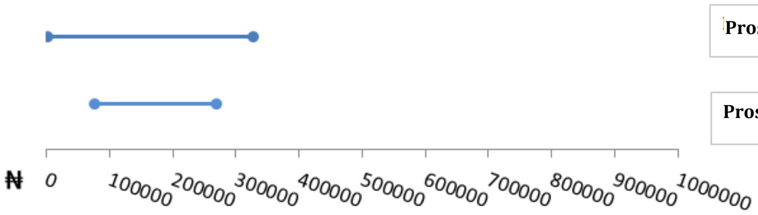
Prospect A (₦23623.65 - ₦39543.3)

or

Prospect B (₦29290.9 - ₦33282.4)

6.

Amount to Firm

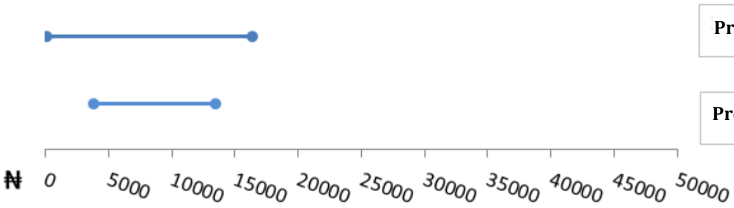


Prospect A (₦0 - ₦326812)

or

Prospect B (₦74652 - ₦267516)

Amount to you



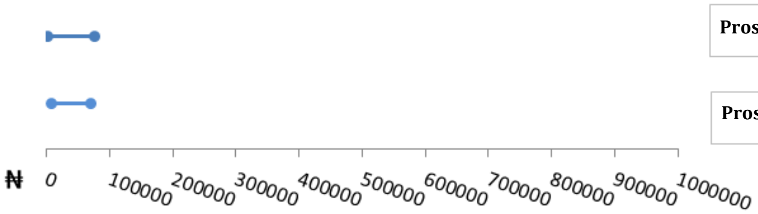
Prospect A (₦0 - ₦16340.6)

or

Prospect B (₦3732.6 - ₦13375.8)

7.

Amount to Firm

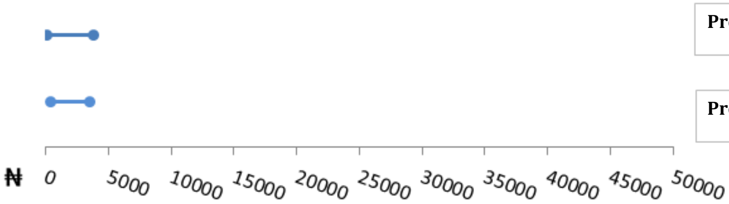


Prospect A (₦0 - ₦75354)

or

Prospect B (₦6663 - ₦68816)

Amount to you



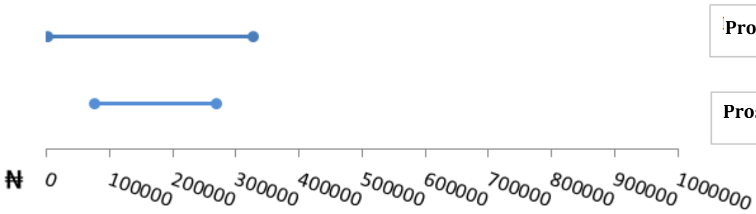
Prospect A (₦0 - ₦3767.7)

or

Prospect B (₦333.15 - ₦3440.8)

6.

Amount to Firm

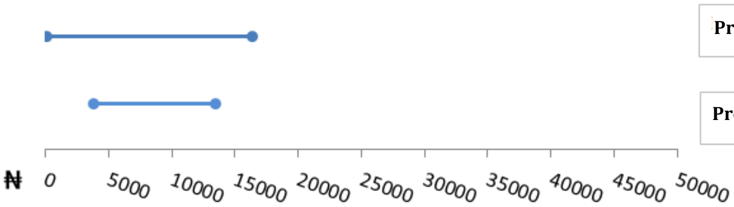


Prospect A (₦0 - ₦326812) ☐

or

Prospect B (₦74652 - ₦267516) ☐

Amount to you



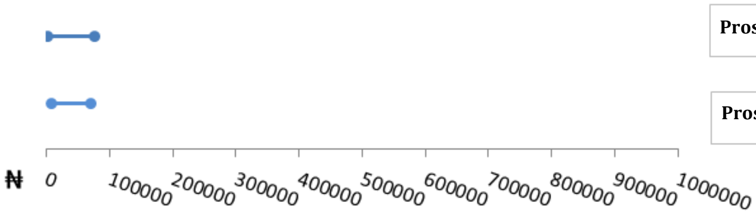
Prospect A (₦0 - ₦16340.6)

or

Prospect B (₦3732.6 - ₦13375.8)

7.

Amount to Firm

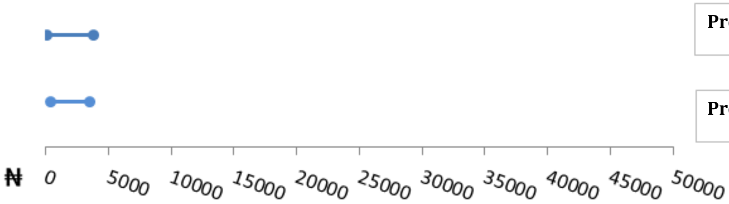


Prospect A (₦0 - ₦75354) ☐

or

Prospect B (₦6663 - ₦68816) ☐

Amount to you



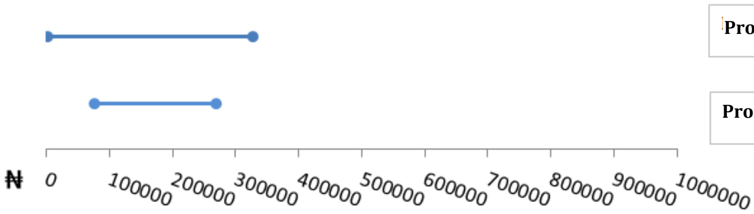
Prospect A (₦0 - ₦3767.7)

or

Prospect B (₦333.15 - ₦3440.8)

6.

Amount to Firm

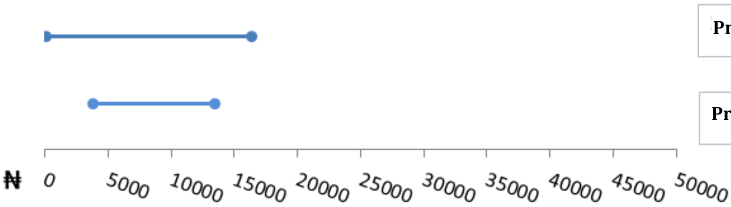


Prospect A (₦0 - ₦326812)

or

Prospect B (₦74652 - ₦267516)

Amount to you



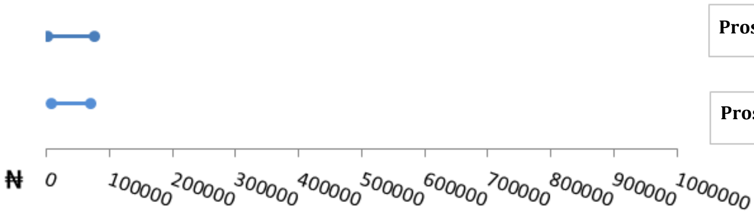
Prospect A (₦0 - ₦16340.6)

or

Prospect B (₦3732.6 - ₦13375.8)

7.

Amount to Firm

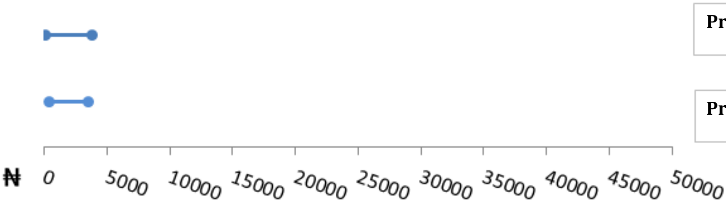


Prospect A (₦0 - ₦75354)

or

Prospect B (₦6663 - ₦68816)

Amount to you

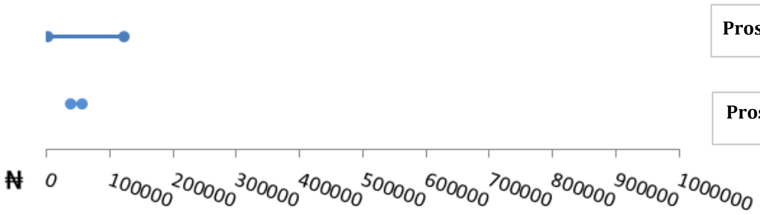


Prospect A (₦0 - ₦3767.7)

or

Prospect B (₦333.15 - ₦3440.8)

10.

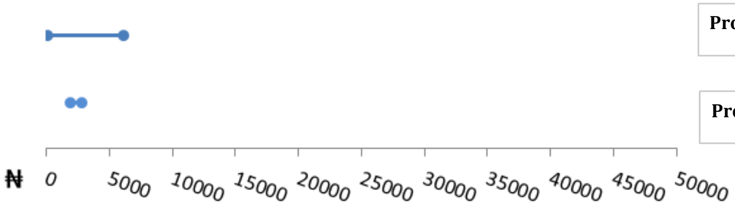


Amount to Firm

Prospect A (₦0 - ₦120624)

or

Prospect B (₦37319 - ₦55849)



Amount to you

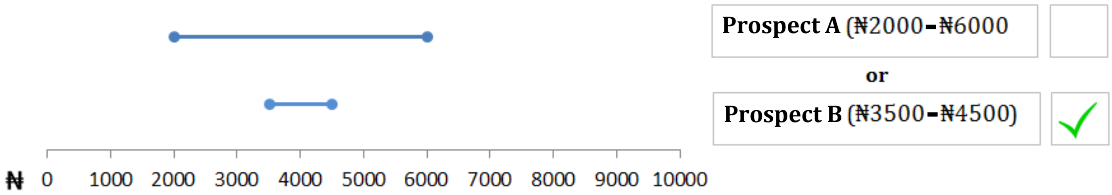
Prospect A (₦0 - ₦6031.2)

or

Prospect B (₦1865.95 - ₦2792.45)

Example: Section D

A farmer was presented with a set of monetary prospects as shown below.



In the case of Prospect A, he was informed he will earn any amount between ₦2000 and ₦6000 which *may or may not be equally likely*.

While for Prospect B he will earn any amount between ₦3500 and ₦4500 which *may or may not be equally likely*.

The farmers choose Prospect B.

This implies that the farmer will earn any amount between ₦3500 and ₦4500 which *may or may not be equally likely*.

In the section that follows, you will be asked similar questions and will be expected to provide you own genuine answer.

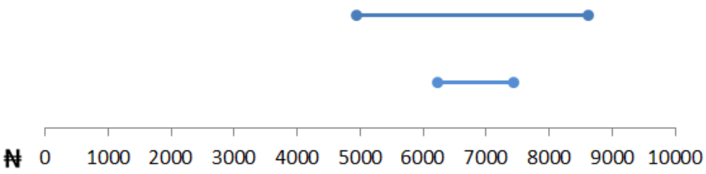
D.

Imagine you are faced with a set of monetary prospects as presented below. In question 1, you *may be or may not be equally likely* to earn any amount between ₦0 and ₦2800) if you choose Prospect A, while for Prospect B you *may be or may not be equally likely* to earn amount between ₦800 and ₦1200. Given that you have to make a choice between prospects A or B which one of the two will you choose?

Note

Provide your answer by ticking the box beside your preferred prospect.

1.

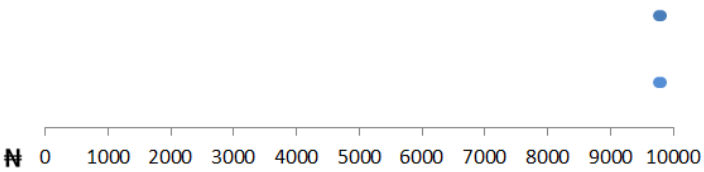


Prospect A (₦4925–₦6226) ☐

or

Prospect B (₦8606–₦7433) ☐

2.

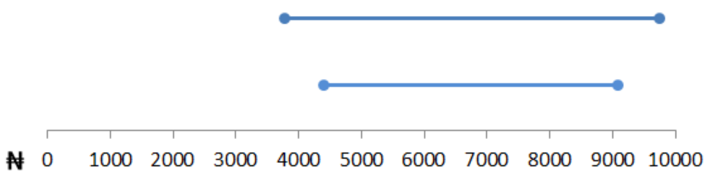


Prospect A (₦9761–₦9804) ☐

or

Prospect B (₦9763–₦9802) ☐

3.

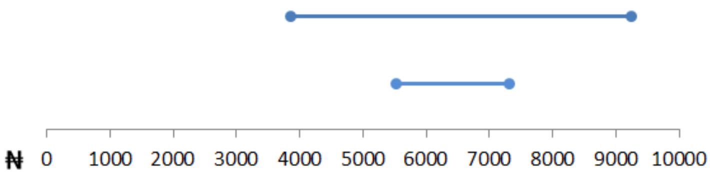


Prospect A (₦3765–₦9737) ☐

or

Prospect B (₦4397–₦9085) ☐

4.

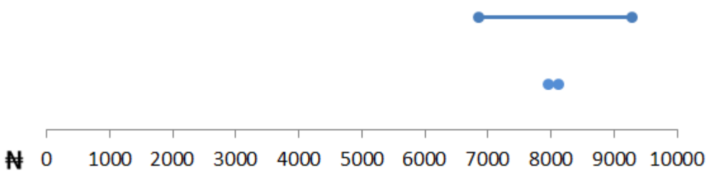


Prospect A (₦3858–₦9241) ☐

or

Prospect B (₦5515–₦7315) ☐

5.

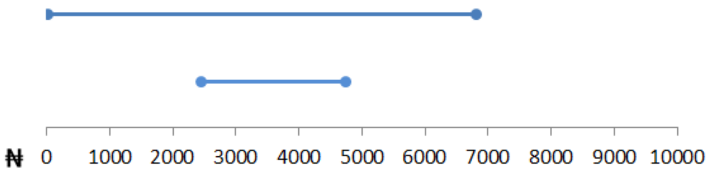


Prospect A (₦6846–₦9271) ☐

or

Prospect B (₦7943–₦8118) ☐

6.

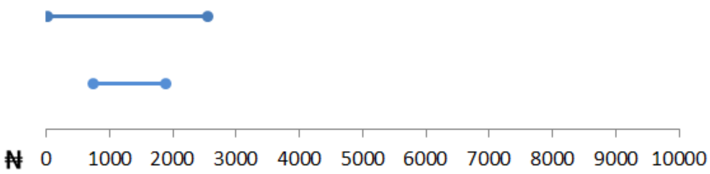


Prospect A (₦0–₦6796) ☐

or

Prospect B (₦2444–₦4726) ☐

7.

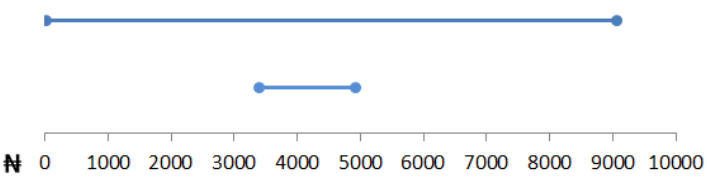


Prospect A (₦0–₦2533) ☐

or

Prospect B (₦731–₦1869) ☐

8.

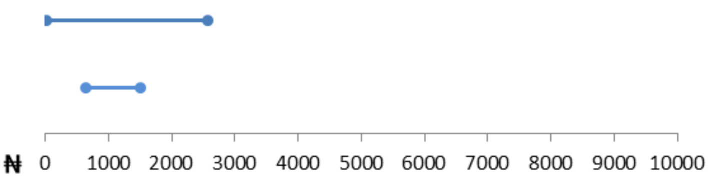


Prospect A (₦0- ₦9047)

or

Prospect B (₦3377- ₦4912)

9.

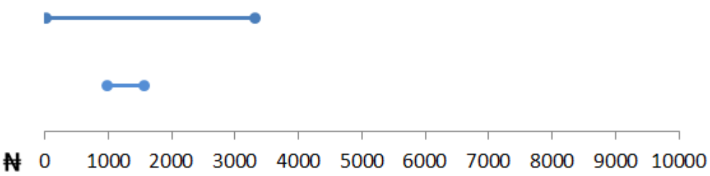


Prospect A (₦0 – ₦9047)

or

Prospect B (₦639 – ₦1503)

10.

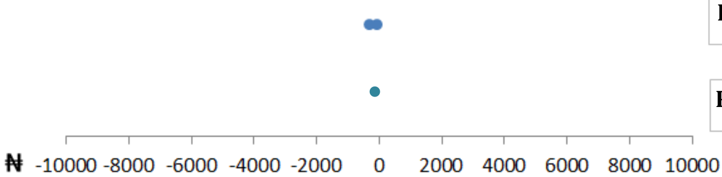


Prospect A (₦0 – ₦3315)

or

Prospect B (₦964 – ₦1566)

11.

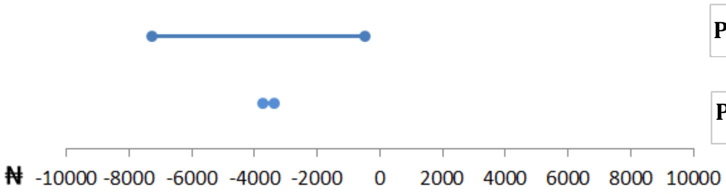


Prospect A (₦-321 – ₦-77)

or

Prospect B (₦-194 – ₦-179)

12.

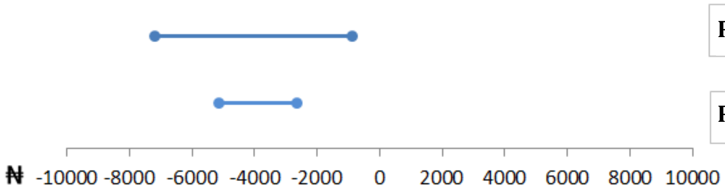


Prospect A (₦-7280–₦-501) ☐

or

Prospect B (₦-3737–₦-3407) ☐

13.

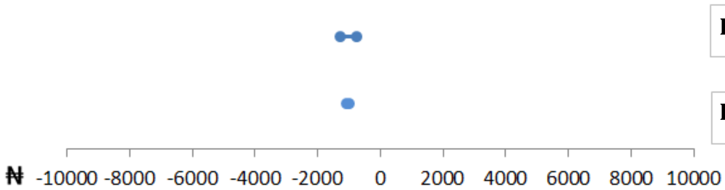


Prospect A (₦-7190–₦-899) ☐

or

Prospect B (₦-5163–₦-2677) ☐

14.

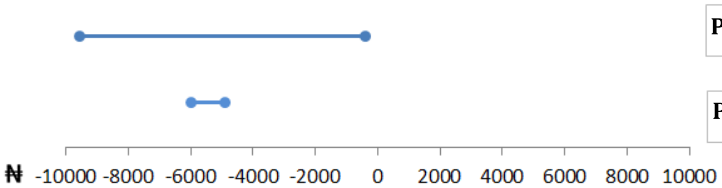


Prospect A (₦-1313–₦-788) ☐

or

Prospect B (₦-1082–₦-1021) ☐

15.

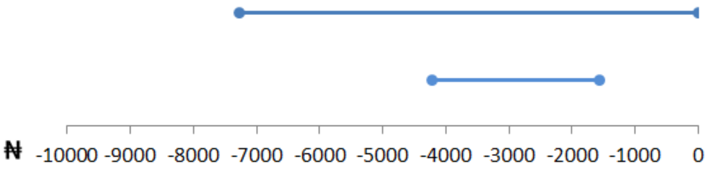


Prospect A (₦-9597–₦-428) ☐

or

Prospect B (₦-6008–₦-4912) ☐

16.

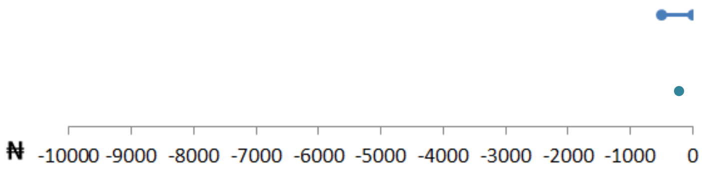


Prospect A (₦-7286–₦0)

or

Prospect B (₦-4220–₦-1582)

17.

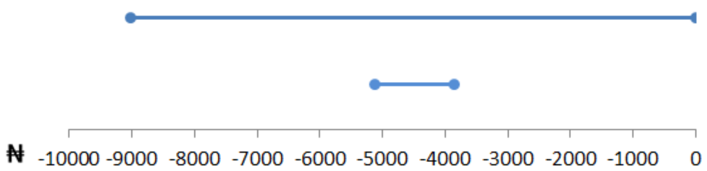


Prospect A (₦-509–₦0)

or

Prospect B (₦-228–₦-208)

18.

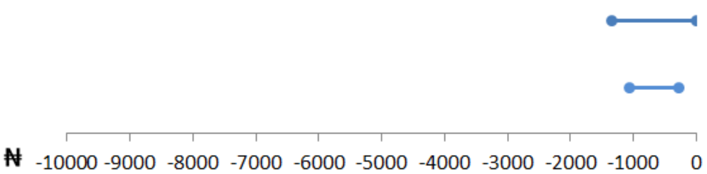


Prospect A (₦--9038–₦0)

or

Prospect B (₦-5125–₦-3867)

19.

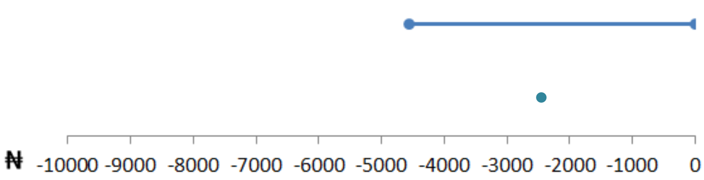


Prospect A (₦-1353–₦0)

or

Prospect B (₦-1073–₦-291)

20.

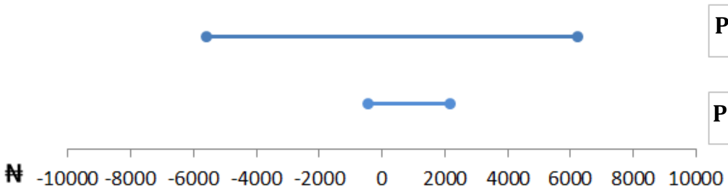


Prospect A (₦-4567– ₦0)

or

Prospect B (₦-2508– ₦-2477)

21.

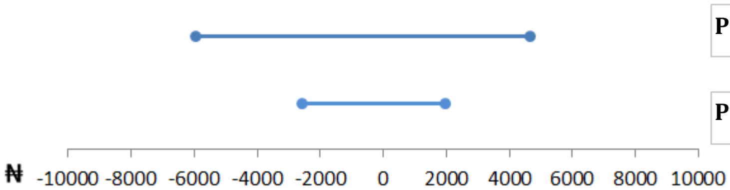


Prospect A (₦-5593– ₦6208)

or

Prospect B (₦-481– ₦2137)

22.

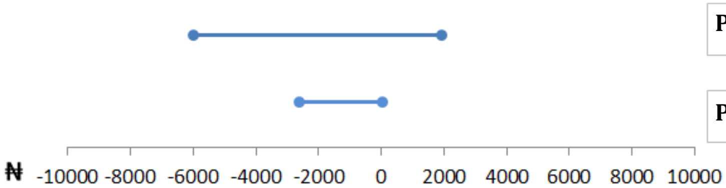


Prospect A (₦--5991– ₦4659)

or

Prospect B (₦-2578– ₦1946)

23.

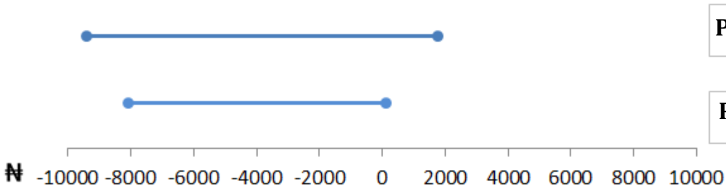


Prospect A (₦-6020– ₦1905)

or

Prospect B (₦-2639– ₦20)

24.

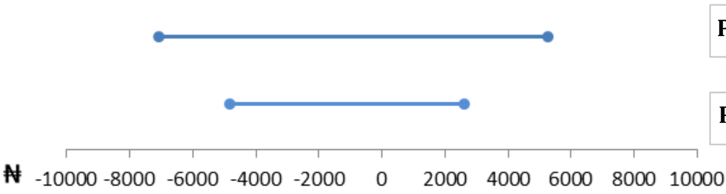


Prospect A (₦-9425–₦1736)

or

Prospect B (₦-8124–₦106)

25.

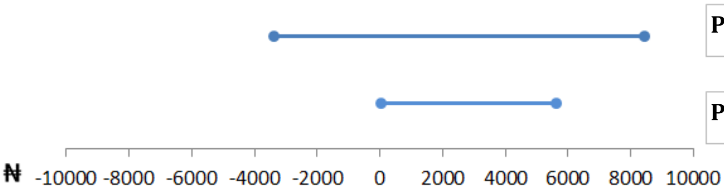


Prospect A (₦-9425–₦1736)

or

Prospect B (₦-8124–₦106)

26.

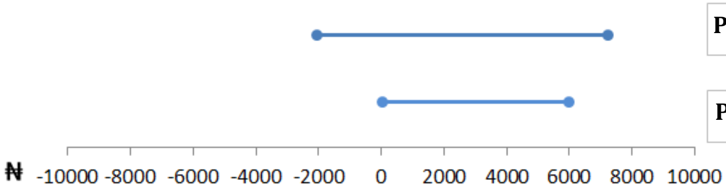


Prospect A (₦-3413– ₦8419)

or

Prospect B (₦0– ₦5590)

27.

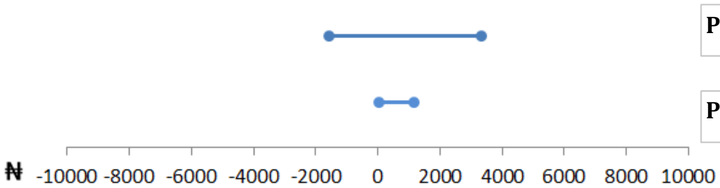


Prospect A (₦-2057–₦7224)

or

Prospect B (₦0–₦5957)

28.

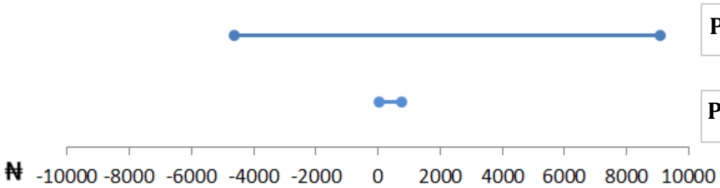


Prospect A (₦-1594– ₦3319) ☐

or

Prospect B (₦0– ₦1136) ☐

29.

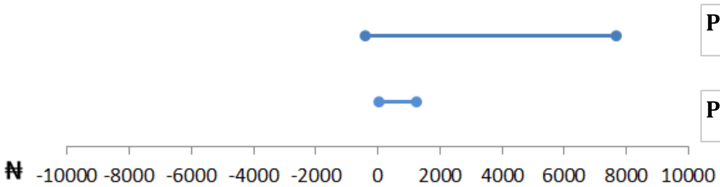


Prospect A (₦-4635–₦9056) ☐

or

Prospect B (₦0– ₦753) ☐

30.

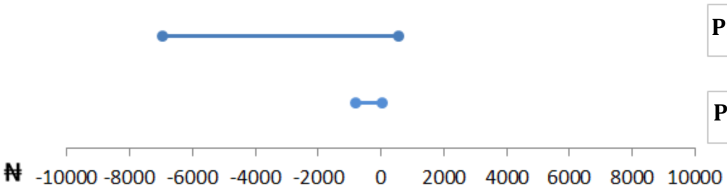


Prospect A (₦-422– ₦7637) ☐

or

Prospect B (₦0– ₦1232) ☐

31.

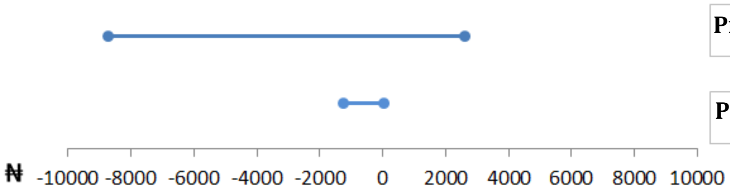


Prospect A (₦-7000– ₦540) ☐

or

Prospect B (₦-820– ₦0) ☐

32.

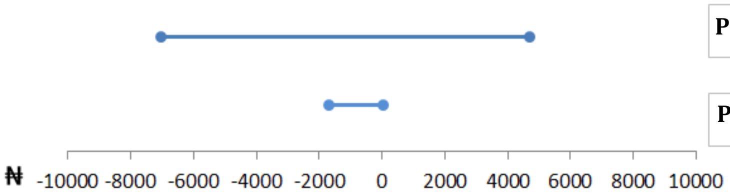


Prospect A (₦-8745–₦2605)

or

Prospect B (₦-1253–₦0)

33.

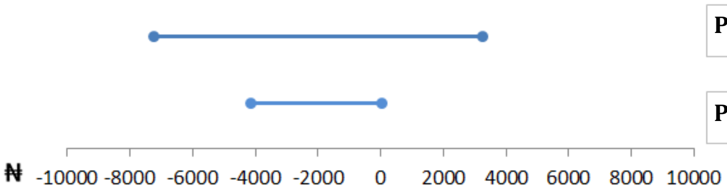


Prospect A (₦-7058–₦4690)

or

Prospect B (₦-1712–₦0)

34.

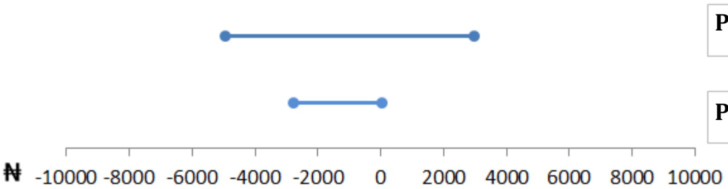


Prospect A (₦-7274–₦3214)

or

Prospect B (₦-4148–₦0)

35.



Prospect A (₦-4954–₦2951)

or

Prospect B (₦-2798–₦0)

E. Mood Evaluation Scale

Please fill in the blank space by choosing the any option from 1-5 as it describes how you feel.

(1) Not at all (2) Just a little (3) Somewhat (4) Moderately (5) Quite a lot (6) Very much

I notice that my mood and/or energy levels shift drastically from time to time___.

I notice that, at times, my mood and/or energy level is very low, and at other times, very high___.

During this ''low'' phase I often feel a lack of energy; a need to stay in bed or get extra sleep; and little or no motivation to do things I need to do___.

I often put on weight during these periods___.

During my low phases, I often feel sad all the time or depressed___.

Sometimes, during these low phases, I have a feeling of low self-confidence___.

My ability to function at work or socially is impaired___.

Typically, these low phases last for a few weeks, but sometimes they last only a few days___.

With this type of pattern I may experience a period of ''normal'' mood in between mood swings, during which my mood and energy level feels ''right'' and my ability to function is not disturbed___.

I may then notice a marked shift or ''switch'' in the way I feel___.

My energy increases above what is normal for me, and I often get many things done they would not ordinarily be able to do___.

Sometimes, during these ''high'' periods, I feel as if they have too much energy or feel ''hyper''___.

During these high periods, I may feel irritable, ''on edge'', or aggressive___.

During these high periods, I take on too many activities at once___.

During these high periods, I become totally confident that everything I do will succeed___.

During these high periods, I may spend money unusually___.

I may be more talkative, outgoing during these periods___.

Sometimes, my behaviour during these high periods seems strange or annoying to others___.

Sometimes, I get into difficulty with others during these high periods___.

How would you describe your general mood today?-----------

F. Mood Evaluation Scale Scoring

The scoring[66] for the test questions as presented in **Mood Evaluation Scale** is:

0 points - Not at all

1 point - Just a little

2 points - Somewhat

3 points - Moderately

4 points - Quite a lot

5 points - Very much

The likelihood of having BD increases with a higher score. Scores for each respondent were cumulated and matched with the screening test scoring ranges:

0-10	No BD Likely
11-18	Possible Mild BD
19-22	Borderline BD
23-37	Mild-Moderate BD
38-56	Moderate - Severe BD
≥ 57	Severe BD

[66] Respondents were not shown this section

G. Socioeconomic Characteristics

1 Age of Respondent: ....

2. Gender............
3. Marital Status............
4. Highest Level of Education Completed............
5. Household Size............
6. Primary occupation? ....
7. Who do you work for in Primary Occupation? ....
8. How long have you been in Primary Occupation? ....
9. How much time do you spend per day in Primary Occupation?
10. Do you have any Secondary Occupation? ....
    If yes proceed to A11
    if no skip questions A11- A17
11. Secondary occupation? ....
12. Who do you work for in Secondary Occupation? ....
13. How long have you been in Secondary Occupation?...........
14. How much time do you spend per day in Secondary Occupation? ....
15. *What is the total size of farm?............
16. Who own the land on which you farm? ....
17. Are you a member of farmers' cooperative? ....

H. Pre-Test Questionnaire Evaluation Sheet

1. Did you understand the questions presented in the questionnaire?

   ____

   (1) Not at all (2) Just a little (3) Somewhat (4) Moderately (5) Quite a lot (6) Very well

   If you choose 1-5 above please proceed to the next question. Otherwise proceed to question 4.

2. What question(s)/section(s) did you not understand?__________
3. What did you not find clear in these question(s)/section(s)_____________
4. Did you find the any question in the Modified Bipolar Spectrum Diagnostic Scale too personal?
5. What suggestions do you have to improve the questionnaire generally?

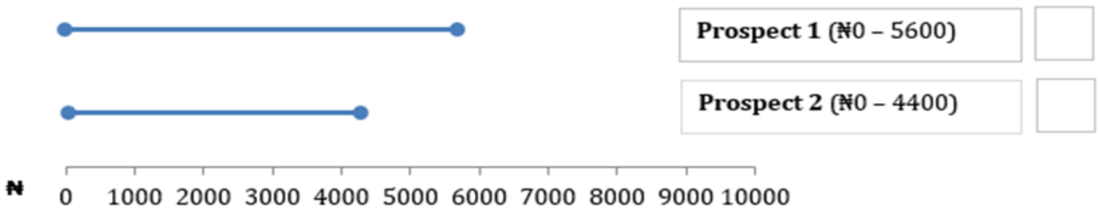
Appendix 4: Follow up Experiment

Dear Respondent,

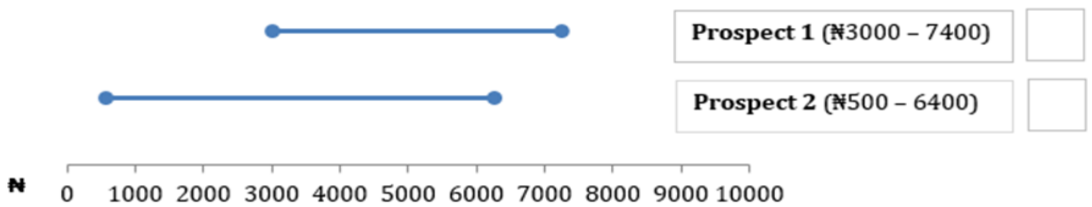
Thank you for participating in this research earlier in the year. I am currently collating results and have summarized your response from the experiments.

As agreed in our previous meeting, I am contacting you regarding the choices you made during the experiment. According to the choices you made earlier, you will Choose Prospect 1 over 2 in the following:

Please confirm if Prospect 1 reflects your personal choice or otherwise.



Please confirm if Prospect 1 reflects your personal choice or otherwise.



In total participants were presented with 5 variants of '*stochastically dominated'* prospects as above. In addition, participants repeated experiments which were flipped version of the main experiment reported in Appendix 4 *i.e.* Prospect B was more 'risky' in terms of wider variance.

Finally, can you provide any reason(s) why you have made this choice?

Thank you for accepting to be contacted once again.

Appendix 5: Procedures for generating prospects*

```
new;
cls;

//Creating the relavant matrices through structures
struct matr {matrix x; matrix ce; matrix dce; matrix count;
             matrix u; matrix s;
                          matrix x_; matrix ce_; matrix dce_; matrix count_;
                          matrix u_; matrix s_};
struct matr c;
c=reshape(c,7,2); // this makes seven instances of this structure
/*
The following code creates 7 type of Lottery Pairs which are uniform on the
interval 0 to 100. In effect it is simply 2 sets of intervals.

- The "left" interval always contains "the" right interval
Thus the left are by nature more "risky".

There are seven "types" created.
Type 1 - in the gain domain unconstrained
Type 2 - in the gain domain, lower bound at zero
Type 3 - in loss domain unconstrained
Type 4 - in the loss domain upper bound at zero
Type 5 - mixed domain, unconstrained
Type 6 - mixed domain - inner gamble lower bound of zero
Type 7 - mixed domain - inner gamble upper bound constrained to zero
*/


accuracy=150; // This sets the accurace which which the expectations are calculated.- 100 is good
beta=1|1;     // The parameters of the beta distribution 1|1 is uniform

//Intitialising the vectors that will contain the zeven types of gambles

/*
The following do loop keeps generating lottery pairs until
all 7 types have at least n pairs
*/

i=1;
n=500;
do until rows(c[1,1].x) eq n and rows(c[2,1].x) eq n and rows(c[3,1].x) eq n
     and rows(c[4,1].x) eq n and rows(c[5,1].x) eq n and rows(c[6,1].x) eq n
         and rows(c[7,1].x) eq n;
top:
t=ceil(.5+6*rndu(1,1));
// The type of pair being generated (1 through 7)
// These two statements randomly generate a lottery pair of a given type
// bound and bound_ are the two lotteries
{lw,up,t1,t2,t3}=make_type(100,t);
{bound,bound_}=genl2(lw,up,t1,t2,t3);
/*
The utilities and certainty equivalents are calculated for the
lottery under 6 "anti-symmetric" power utilities
*/
```

```
//This is for the outer lottery
{u11,c11}=choquet_beta(bound,beta,2|2,accuracy);
{u12,c12}=choquet_beta(bound,beta,1.25|1.25,accuracy);
{u13,c13}=choquet_beta(bound,beta,.99|.99,accuracy);
{u14,c14}=choquet_beta(bound,beta,.5|.5,accuracy);
{u15,c15}=choquet_beta(bound,beta,.1|.1,accuracy);
{u16,c16}=choquet_beta(bound,beta,.05|.05,accuracy);

//This is for the inner lottery
{u21,c21}=choquet_beta(bound_,beta,2|2,accuracy);
{u22,c22}=choquet_beta(bound_,beta,1.25|1.25,accuracy);
{u23,c23}=choquet_beta(bound_,beta,.99|.99,accuracy);
{u24,c24}=choquet_beta(bound_,beta,.5|.5,accuracy);
{u25,c25}=choquet_beta(bound_,beta,.1|.1,accuracy);
{u26,c26}=choquet_beta(bound_,beta,.05|.05,accuracy);

x=bound|bound_; // These are the lottery boundaris for the pair

/*Here there would have to be a difference in the sign of the difference between the
CEs betwen alpha=2|2 and alpha=0.05 - otherwise there would be no difference
in the decision made by agents
- if this is not the case we do not record this pair*/
if  (c11-c21)*(c16-c26) >0;
        goto top;
endif;

//Recording each of the lottery pair types
//Bounds followed by differences in ce by the 6 different alpha types

if rows(c[t,1].x) < n;
        c[t,1].x=c[t,1].x|bound'; //The outer prospect
        c[t,2].x=c[t,2].x|bound_'; //The inner prospect
        c[t,1].ce=c[t,1].ce|(c11~c12~c13~c14~c15~c16); //ce for the outer prospect
        c[t,2].ce=c[t,2].ce|(c21~c22~c23~c24~c25~c26); //ce for the inner prospect
        c[t,1].u=c[t,1].u|(u11~u12~u13~u14~u15~u16);   //utility for the outer prospect
        c[t,2].u=c[t,2].u|(u21~u22~u23~u24~u25~u26);   //utility for the inner prospect
        c[t,1].dce=c[t,1].ce-c[t,2].ce;                // difference in ces for outer and innner prospects
endif;
i=i+1;
endo;


/*Because the zero boundaries may occur in unconstrained types 1 3 and 5
we will need eliminate these*/
for t (1,7,1);
        c[t,1].s=zeros(rows(c[t,1].x),1);
endfor;
c[1,1].s=c[1,1].x[.,1] .eq 0;
c[3,1].s=c[3,1].x[.,2] .eq 0;
c[5,1].s=(c[5,2].x[.,1] .eq 0) .or (c[5,2].x[.,2] .eq 0);

for t (1,7,1);
        for j (1,2,1);
```

```
        c[t,j].x=delif(c[t,j].x,c[t,1].s);
        c[t,j].ce=delif(c[t,j].ce,c[t,1].s);
        c[t,j].u=delif(c[t,j].u,c[t,1].s);
        endfor;
        c[t,1].dce=delif(c[t,1].dce,c[t,1].s);
endfor;


/*c[i,1].count is the the number of
  times the difference in certainty equivalents were positive depending on alpha
  It is done for each of the 7 types of lottery pairs
 */
 for t (1,7,1);
        c[t,1].count=c[t,1].count|sumc(c[t,1].dce' .>0);
        for j (1,2,1);
                c[t,j].x=c[t,j].x~c[t,1].count;
                c[t,j].ce=c[t,j].ce~c[t,1].count;
                c[t,j].u=c[t,j].u~c[t,1].count;
        endfor;
        c[t,1].dce=c[t,1].dce~c[t,1].count;
endfor;



//*now they are sorted by the the last column (the count, which is then removed)
for t (1,7,1);
        for j (1,2,1);
                c[t,j].x=sortc(c[t,j].x,cols(c[t,j].x));
                c[t,j].x=c[t,j].x[.,1:cols(c[t,j].x)-1];
                c[t,j].ce=sortc(c[t,j].ce,cols(c[t,j].ce));
                c[t,j].ce=c[t,j].ce[.,1:cols(c[t,j].ce)-1];
                c[t,j].u=sortc(c[t,j].u,cols(c[t,j].u));
                c[t,j].u=c[t,j].u[.,1:cols(c[t,j].u)-1];
        endfor;
        c[t,1].dce=sortc(c[t,1].dce,cols(c[t,1].dce));
        //c[t,1].dce=c[t,1].dce[.,1:cols(c[t,1].dce)-1];
        c[t,1].count=sortc(c[t,1].count,1);
endfor;

 //Here are the subsets of the larger matrices below
for t (1,7,1);
        for j (1,2,1);
                c[t,j].x_=thread(c[t,j].x,c[t,1].count);
                c[t,j].u_=thread(c[t,j].u,c[t,1].count);
                c[t,j].ce_=thread(c[t,j].ce,c[t,1].count);
        endfor;
        c[t,1].dce_=thread(c[t,1].dce,c[t,1].count);
endfor;

  "The subset lotteries are by type";
  for t (1,7,1);
  c[t,1].x_~c[t,2].x_;
  endfor;
```

```
/*____________________________________________________________________________*/
/* The following are the procedures used above*/
// Calculating Expected utility under generalised beta distribution
proc(2)=choquet_beta(bound,beta,alpha,accuracy);
local z,x,u,mu,ce;
// bound 2 by 1 vector - lower bounds then upper bound
// beta  2 by 1 vector for beta distribution
// alpha 2 by 1 vector for the power utilities (upper and lower)
// accuracy - higher the better, but will take more time
if accuracy eq miss(1,1);
                accuracy=100;
endif;
z=(1/2+seqa(0,1,accuracy))/accuracy;
x=bound[1,.]+(bound[2,.]-bound[1,.])*z;
//x=bound[1,.]+(bound[2,.]-bound[1,.])*cdfBetaInv(z,beta[1,.],beta[2,.]);
u=uf(x,alpha);
mu=meanc(u);
ce=cef(mu,alpha);
//mu is the choquet expected utility
//ce is the certainty equivalent
retp(mu,ce); endp;

//Calculating Choquet expectation the long way- very slow
proc(2)=choquet_beta2(bound,beta,alpha);
local g,n,d,mn,mx,s,s_,u,u_,p,p0,ce,lw,up,sg;
g=uf(bound,alpha);
n=100;
d=(maxc(g)-minc(g));
mn=(bound[1,.] .>0)*bound[1,.];
mx=(bound[2,.] .<0)*bound[2,.];
s=minc(g)+d*seqa(0,1,n+1)/(n);
sg=(s .>0);
s_=cef(s,alpha);
u=uf(s,alpha);
p= 1-cdfbetag(s_,bound[1,.],bound[2,.],beta[1,.],beta[2,.]);
p0=(s .<0).*(p-1)+ (s .>0).*p;
u_=uf(mn,alpha)+uf(mx,alpha)+sumc(p0*d/(n));
ce=cef(u_,alpha);
//mu is the choquet expected utility
//ce is the certainty equivalent
retp(u_,ce); endp;

//Code for the Cdf for generalised Beta Distribution
//See notes
proc(1)=cdfbetag(x,l,u,beta1,beta2);
        //l is lower bound, u is upper bound
        //beta1 and beta2 are the coefficients of the beta distribution
        local s,t,z;
        x=(x-l)./(u-l);
        s=(x .ge 0 .and x .le 1 );
        t=(x .> 1);
        z=x.*s + t;
retp(cdfbeta(z,beta1,beta2)); endp;
```

```
//Power utility - without loss aversion
proc(1)=uf(u,alpha);
        local x,s;
        s=(u .>0) - (u.<0);
        x=s.*((s.*u).^(alpha'));
        x= (u.<0).*x[.,1]+ (u.>0).*x[.,2];
retp(x); endp;




//Certainty Equivalent of Power Utility - without loss aversion
proc(1)=cef(u,alpha);
        local x,s;
        s=(u .>0) - (u.<0);
        x=s.*((s.*u).^(1/alpha'));
        x= (u.<0).*x[.,1]+ (u.>0).*x[.,2];
retp(x); endp;


//The make typ has seven type of lotteries outlined above.

proc(5)=make_type(scale,num);
        local t1,t2,t3,lw,up;
        t3=0;
        if num eq 1;
               t1=0;  t2=0; lw=0; up=scale;
               elseif num eq 2;
               t1=-1; t2=0; lw=0; up=scale;
               elseif num eq 3;
               t1=0; t2=0; lw=-scale; up=0;
               elseif num eq 4;
               t1=1; t2=0; lw=-scale; up=0;
           elseif num eq 5;
               t1=0; t2=0; lw=-scale; up=scale;  t3=2;
               elseif num eq 6;
               t1=0; t2=-1; lw=-scale; up=scale; t3=1;
               elseif num eq 7;
               t1=0; t2=1; lw=-scale; up=scale; t3=-1;
        endif;

retp(lw,up,t1,t2,t3); endp;



proc(2)=genl2(lw,up,t1,t2,t3);
// Generates a pair of non dominated lotteries
        local lw1,up1,lw2,up2,u;

        tp:
        {lw1,up1}=genl(lw,up,t1);//the outer
```

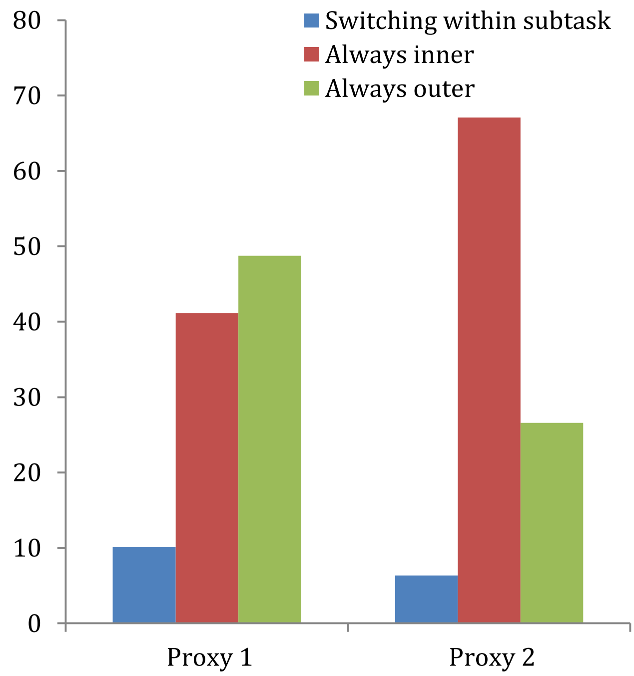
```
    if t3 ne 0;
          if lw1*up1 ge 0; goto tp; endif;
   endif;

    if t3 eq -1;
               {lw2,up2}=genl(lw1,0,t2);// the inner
               elseif t3 eq 2;
               {lw2,up2}=genl(lw1,up1,t2);
               if lw2*up2 ge 0; goto tp; endif;
               elseif  t3 eq 1;
          {lw2,up2}=genl(0,up1,t2);// the inner
               elseif t3 eq 0;
          {lw2,up2}=genl(lw1,up1,t2);
        endif;

        if lw1 eq lw2 and up1 eq up2;
        goto tp;
        endif;

retp(lw1|up1,lw2|up2); endp;

proc(2)=genl(lw,up,t);
local lbout,ubout,d;

        d=up-lw;
        if t eq -1;
               //exactly at the lower bound
            lbout=lw;
               d=up-lbout;
               ubout=round(lbout+d*rndu(1,1));
               elseif t eq 1;
               //exactly at the upper bound
               ubout=up;
               d=ubout-lw;
               lbout=round(ubout-d*rndu(1,1));
               elseif t eq 0;
               //anywhere inside the upper and lower bounds
               lbout=round(lw+d*rndu(1,1));
               d=up-lbout;
               ubout=round(lbout+d*rndu(1,1));
               elseif t eq miss(1,1);
               //exactly specified
               lbout=lw;
               ubout=up;
        endif;

retp(lbout,ubout); endp;
stop;
```

```
proc(1)=thread(y1,c1);
        local z1,i,j;
z1=y1[1,.];
i=1;
j=1;
do until j>rows(y1);
   if c1[j,1] eq i+1;
   z1=z1|y1[j,.];
   i=i+1;
   endif;
   j=j+1;
endo;
retp(z1); endp;
```

*I acknowledge my supervisor Professor Kelvin Balcombe for sharing these codes.

Appendix 6: Descriptive Statistics

For the proxy-gain subtasks, participants' made decision on behalf of others on tasks in the gain only domain to permit comparison between the monetary decision for oneself *versus* others; thus the design followed the monetary decision for self in the gain domain (*i.e. Types 1 & 2*) presented in **Figure 2** in Chapter 5. The result presented in **Figure 13** show that 54% (resp., 71%) for *Type1* (resp., *Type2*) subtask picked the outer (resp., inner) prospect overall. An examination of the proxy subtasks show that of this overall proportion, 48% constantly chose the outer prospect for *Proxy1* while 67% consistently picked the inner prospect for *Type2*.



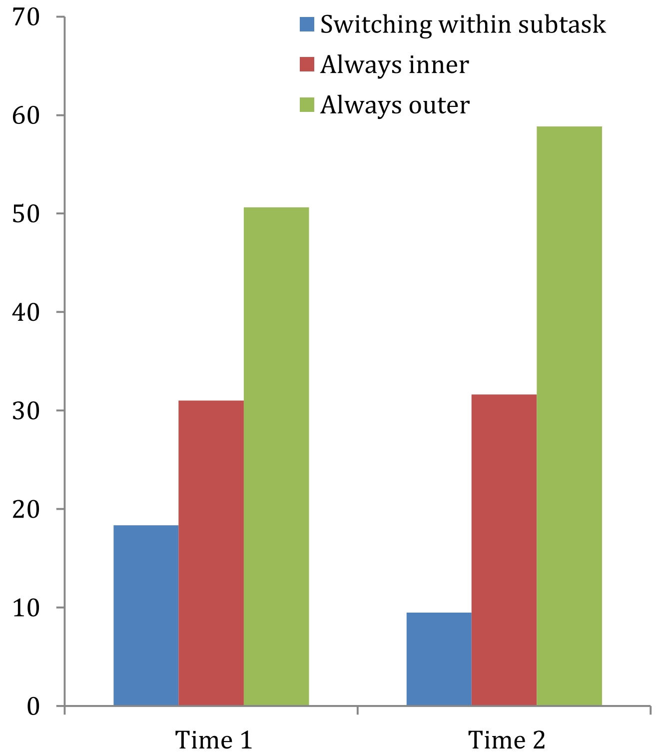
Note. ***Proxy1*** *= Type 1 - unconstrained in the gain domain,* ***Proxy2*** *= Type 2 - upper bound of the outer prospect at zero in the gain domain*

Figure 41. Choice by subtask type for proxy-gain under risk.

McNemar's test to determine the significance in the overall choices farmers made in the *Type1* and *Type2* subtasks under risk however show statistical significant difference in both choices at the 1% level ($\chi^2 = 149$, $p < 0.001$) thus the hypothesis that there is marginal homogeneity in the aggregate choices of farmers within a specific content domain is rejected.

Finally, paired t-test to determine whether choices farmers made in the *self* and *Proxy* tasks under risk show statistical significant difference between both choices at the 1% level ($t(1579)=-4.89$, $p<0.001$) thus the hypothesis that there is no significant difference in a DM's choice pattern under personal and proxy context is rejected. However under uncertainty, the hypothesis that there is no significant difference in a DM's choice pattern under personal and proxy context cannot be rejected at 1% level ($t(1579)=1.03$, $p=0.301$).

As for switching behaviour by subtask type for time under risk, a histogram of the time subtasks is presented in **Figure 14.** Recall in Chapter 5 for time context, participants' made decision on time tasks in the loss only domain to permit comparison between the monetary decisions *versus* time; thus the design followed the monetary decision in the loss domain (*i.e. Types 3 & 4*) presented. The results presented in **Figure 14** indicate that the choice made under time context has some similarities to monetary context in the loss domain.



Note. ***Time1*** *= Type1 - unconstrained in the loss domain,* ***Time2*** *= Type 2 - lower bound of the outer prospect at zero in loss domain*

Figure 42. Switching behaviour by subtask type for time under risk.

There was a strong preference for the outer prospect among participants in the time context. This is evident from 50% and 58% of participants' for *Type3* and *Type4* respectively that never switched choice in the loss domain along the entire experiment. McNemar's test to determine significance in the overall choices farmers made in the *Type3* and *Type4* subtasks under risk however show no statistical significant difference in both choices at the 10% level, ($\chi^2 = 0.70$, $p = 0.402$). Thus, the hypothesis that there is marginal homogeneity in the aggregate choices of farmers within a specific content domain cannot be rejected.

Finally, paired t-test to determine whether choices farmers made in the *monetary* and *time* framed tasks under risk show no statistical significant difference between both choices at the 10% level, $t(1579)=-0.99$, $p=0.321$ thus the hypothesis that there is no significant difference in a DM's choice pattern under personal and proxy context cannot be rejected. However under uncertainty, the hypothesis that there is no significant difference in a DM's choice pattern under personal and proxy context is rejected at 10% level, $t(1579)=2.46$, $p=0.014$).

Appendix 7: Stochastic dominance

In the decision theory literature, stochastic dominance is a type of ordering (*albeit* partial) by which prospects with different probabilistic outcomes are ranked.

First order stochastic dominance (FODs)

Given two prospects A and B having CDFs FA and FB. Suppose prospects A and B have a bounded support $[0, \infty]$ such that $A(0) = B(0) = 0$ then prospect A first-order stochastically dominates B when a DM that maximizes expected utility prefer A to B *iff*

$$A(x) \leq B(x) \quad for\ all\ values\ of\ x$$

Provided the DM's utility function (u) is non-decreasing $u\colon \mathbb{R} \to \mathbb{R}, iff\ A$ first-order stochastically dominates B

$$U(A) = \int u(x)\, dA(x) \geq \int u(x)\, dB(x) = U(B)$$

Second order stochastic dominance (SODs)

While FOSD implies SOSD, the reverse does not necessarily apply. As for second order stochastic dominance, A SOSD B *iff*

$$\int_0^{\overline{x}} B\ (x)dx \geq \int_0^{\overline{x}} A\ (x)dx \text{ for all values of } \overline{x}\ \in [0, \infty]$$

Given the two prospects A and B having CDFs F_A and F_B, assuming

$$\int_0^{\infty} u(x)\ F_B(x)dx \geq \int_0^{\infty} u(x)\ F_A(x)dx\ \ for\ all\ values\ of\ x$$

and $F_B(x^*) -\ F_A(x^*)$ for some x^* then prospect A dominates B from the position of second-order stochastic dominance (SODs).

Appendix 8: Obtaining CEU under probability warping

The link between non-linear mathematical expectation and probability measure referred to the Choquet expectation is denoted by

$$\int f dv = \int_{-\infty}^{0} [v(\{s \in S \,|U(f(s)) \geq z\}) - 1]dz$$
$$+ \int_{0}^{\infty} v(\{s \in S|U(f(s)) \geq z\})dz \qquad (3.4.21)$$

Representing outcome in *equation* (3.4.21) under state s by $f(s) = s$ gives

$$\int f dv = \int_{-\infty}^{0} [v(\{s \in S \,|U(s) \geq z\}) - 1]dz$$
$$+ \int_{0}^{\infty} v(\{s \in S|U(s) \geq z\})dz \qquad (3.4.22)$$

In the case where it is established v is a true probability distribution then *equation* (3.4.21) reduces to

$$v(\{s \in S\}: U(s) > z) = 1 - F_s(U^{-1}(z)) \qquad (3.4.23)$$

where F_s is the cumulative distribution function of s.
The expected utility is given as

$$V = E_s(U) = \int_{-\infty}^{\infty} U(s) dF_s(s) \qquad (3.4.24)$$

Suppose the distribution of the prospect outcomes follow a generalised beta[67]

$$s \sim f_{gbeta}(s|\alpha, \beta, l, q)$$

Then

$$U(s) > z \;\Rightarrow s > U^{-1}(z) \qquad (3.4.25)$$

Thus

$$v(\{s\}: U(s) > z) = 1 - F_{gbeta}(U^{-1}(z)|\alpha, \beta, l, q) \qquad (3.4.26)$$

[67] Given P which represents an absolutely continuous random variable on the interval [0,1], P is characterised by a Beta distribution with shape parameters α and β in the case where its PDF $f(p)$ is defined as $f_p(p) = \begin{Bmatrix} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha,\beta)} \\ 0 \; otherwise \end{Bmatrix}$

Where a generalised Beta distributed random variable is $s = l + p(q - l) \; where \; x \sim f_{gbeta}(p|\alpha, \beta)$

Thus $f_{gbeta}(s|\alpha, \beta, l, q) = \frac{f_{beta}\left(\frac{s-l}{q-l}|\alpha,\beta\right)}{q-l}$

Rearranging the above equation,

$$v(\{s\}: U(s) > z) = 1 - F_{gbeta}\left(\frac{U^{-1}(z) - q}{q - l} | \alpha, \beta\right) \qquad (3.4.27)$$

Obtaining the EU therefore, is possible from estimating the equation

$$V = \int_{l}^{q} U(s) dF_{gbeta}(s|\alpha, \beta, l, q) \qquad (3.4.28)$$

$$V = \int_{0}^{1} U(l + x\,(q - l)) dF_{gbeta}\left(\frac{x - l}{q - l} | \alpha, \beta\right) \qquad (3.4.29)$$

Appendix 9: Statistics on Bipolar Disorder in Nigeria

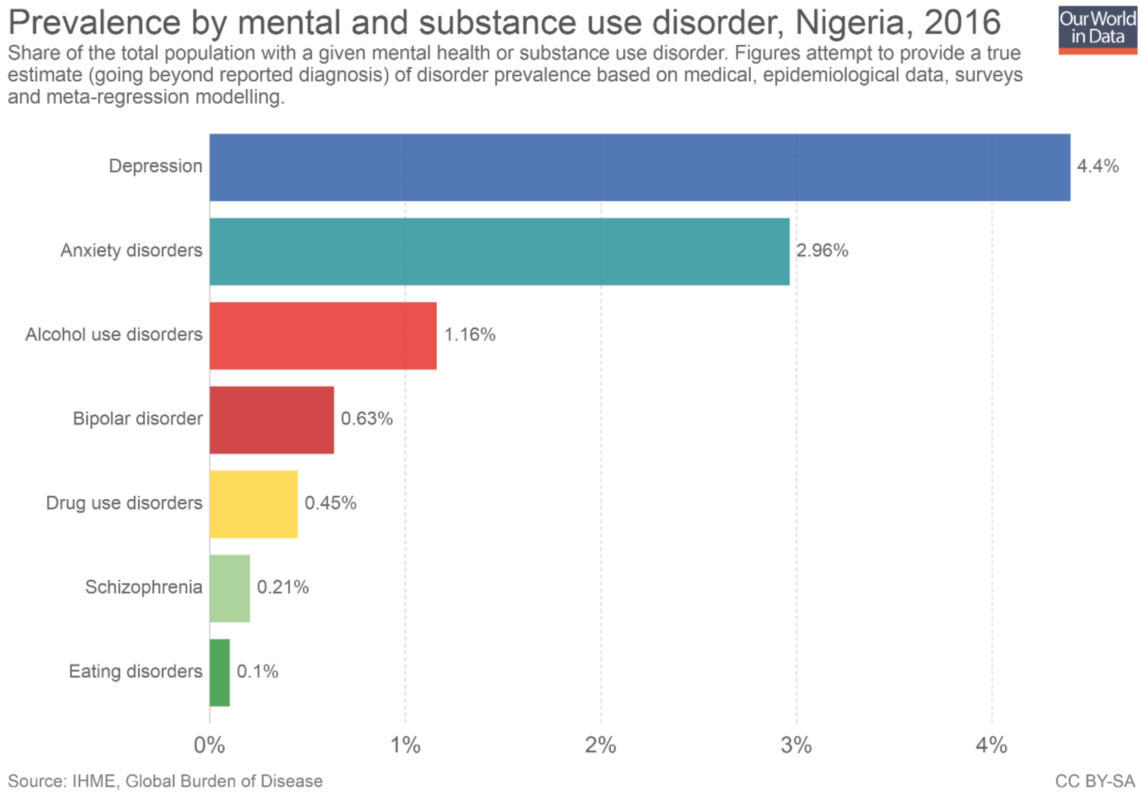


Figure 43. The ranking of bipolar disorder with other disorders in Nigeria

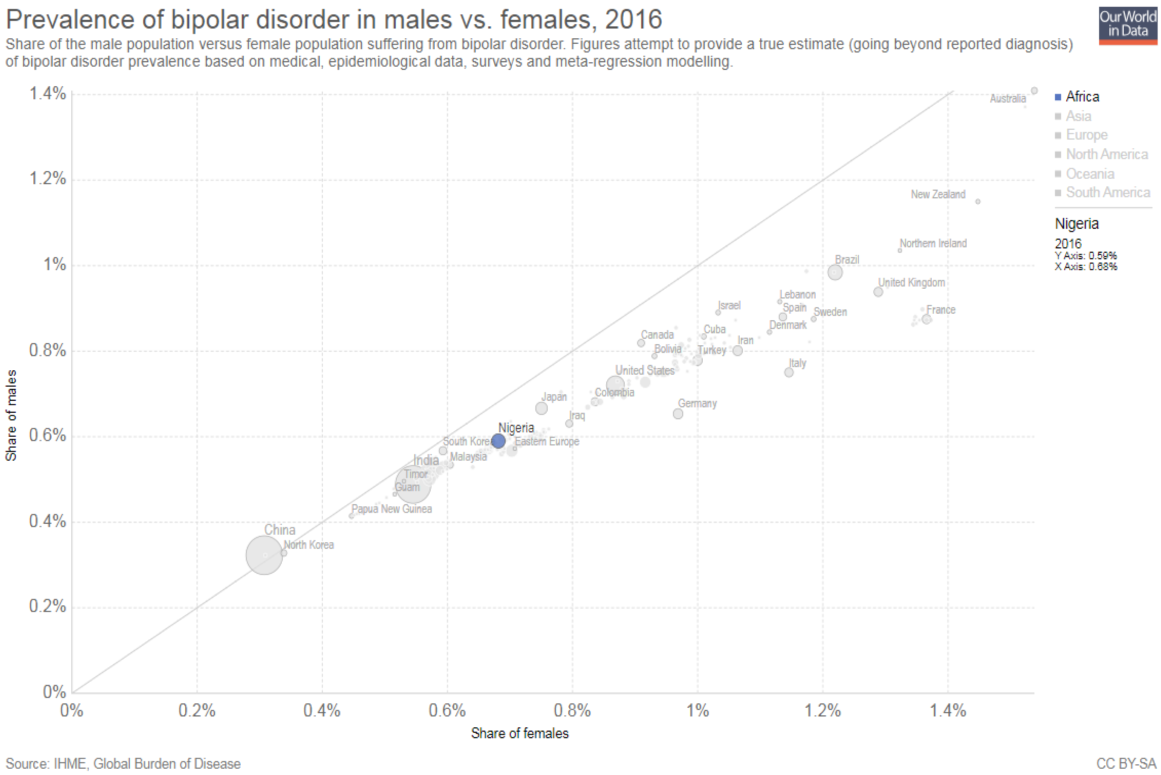


Figure 44. The prevalence of bipolar disorder in by gender Nigeria

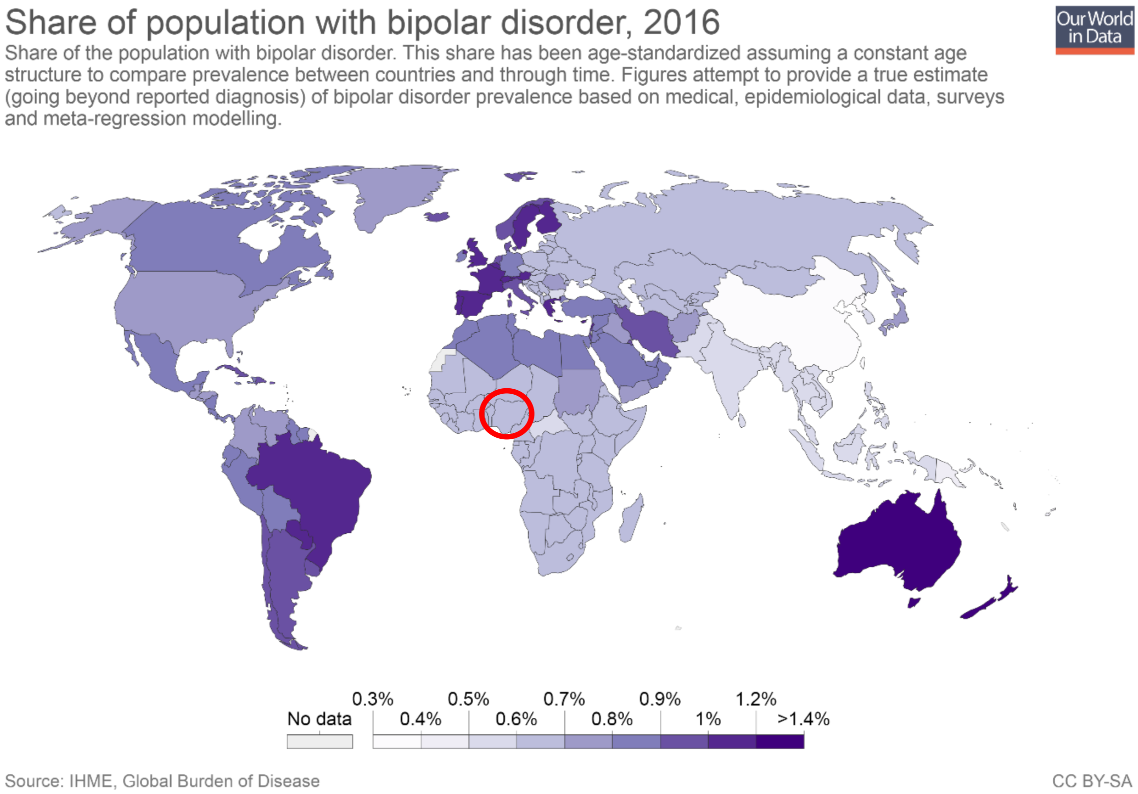


Figure 45. The proportion of the population with bipolar disorder in Nigeria

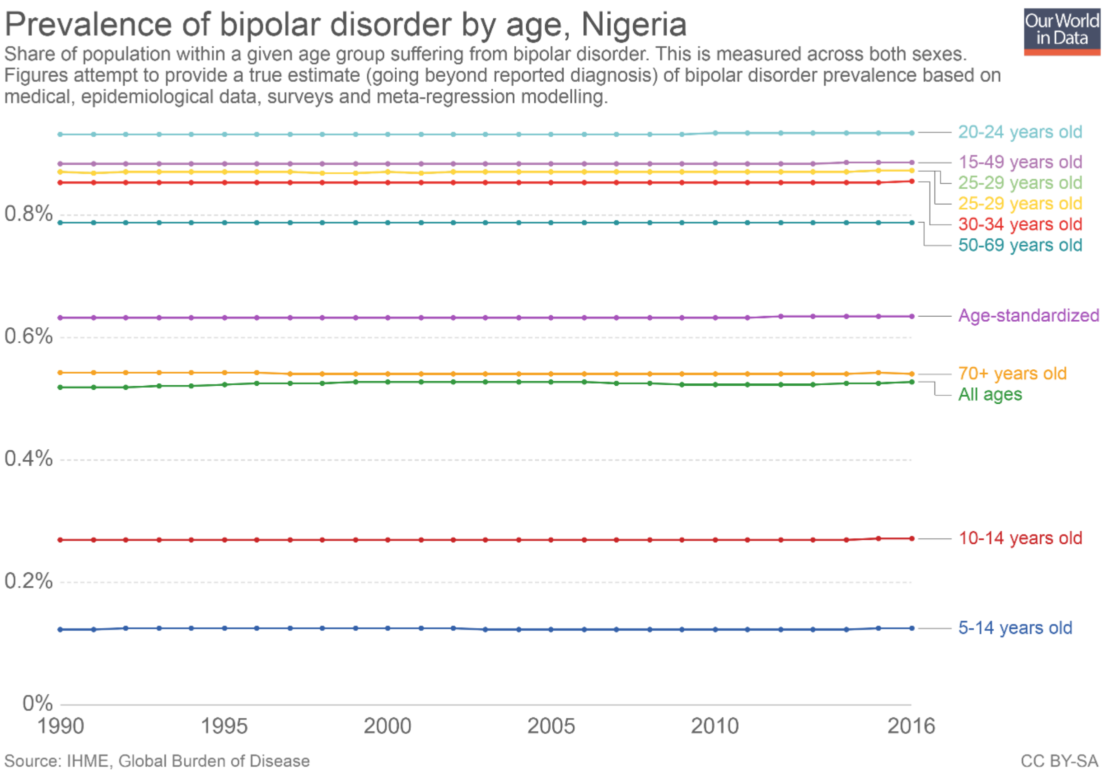


Figure 46. The prevalence of bipolar disorder by age in Nigeria.

Appendix 10: Pilot survey results and discussion

Recall that a pilot survey was conducted to determine how well the questions were understood, whether the content of each question was consistently given the same meaning by each respondent and most importantly if the main experiment was feasible. In order to achieve these objectives of conducting the pilot, 30 farmers randomly selected from two communities via a recruitment process facilitated through extension agents and community leaders participated in the experiment. The results presented here describes participants' choices under risk and uncertainty when presented with the pilot experiment described in Chapter 5.

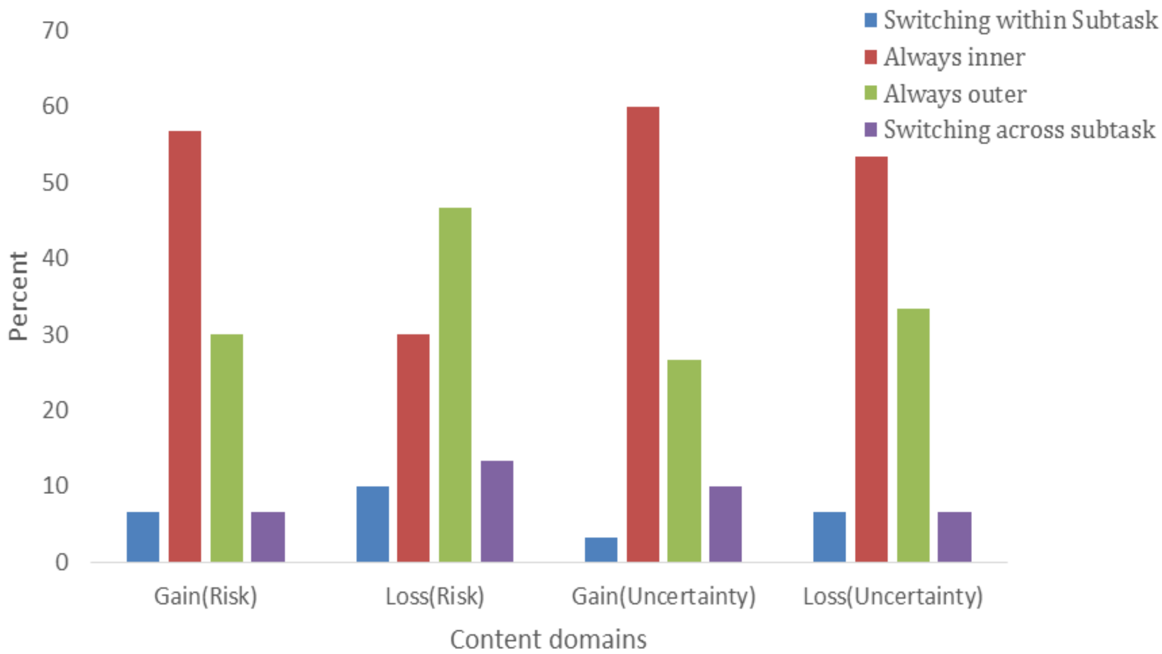


Figure 47. Participants' patterns of behaviour under different conditions and content domains

In the gain domain, participants that switched within subtask for risk were approximately 7%. This statistic suggests that extreme risk preference among majority of participants' as over 57% did not switch from the 'safer' prospect B. As for participants' choices across subtasks, only about 7% switched. The proportion of participants' choices under uncertainty also presented in Figure 47 show that those who switched within subtask were approximately 3% while 10% switched across subtasks. Notably, a larger proportion under uncertainty (accounting for 60%) compared to risk did not switch at all *i.e.* they consistently choose the inner prospect (prospect B) for all gain domain tasks. This behaviour suggest that both for risk and uncertainty, participants at the aggregate level find the inner prospect more attractive for gains. Since the inner prospect is by nature less “risky”, this finding might be an indication of participants’ dislike for risk and (and even greater dislike for) uncertainty in the gain domain. These findings are in line with what was reported using data obtained from the main experiment.

In the loss domain task (Types 3 & 4), there was switching within subtask under risk by 10% of the participants while 13% switched across subtasks. However, for uncertainty 7% switched within subtasks and across tasks as shown in Figure 47. Unlike the gain domain where the inner prospect was largely preferred, prospect choice in the loss domain was the outer prospect. Notably, 47% in the case of risk and 33% under uncertainty did not switch at all (*i.e.* these group consistently chose only the outer prospect along all loss domain tasks) thereby portraying extreme risk/uncertainty seeking behaviour. These findings are indications that both under risk and uncertainty, participants at aggregate level consider the outer prospect more attractive for losses. Again, since the outer prospect is by design more “risky”, these choice patterns are possible indicators of participants’ risk and uncertainty seeking in the loss domain.

The main differences between the results of the pilot and the main study was that the proportion of participants that violated monotonic switching was higher in for the former compared to the latter. In addition, there was more switching within subtask in the main experiment. Although these identified differences were not subjected to further statistical tests, it is surmised that the incorporation of feedback discussed in 5.3.4 in Chapter 5 might have contributed to improving the quality of the data.

Finally, we asked participants to provide reason the main reason that influenced their choice of prospects. As presented in Figure 48, about 80% percent mentioned the size of the prospects and 3% reporting the mood during the experiment as the main driver of their decision.

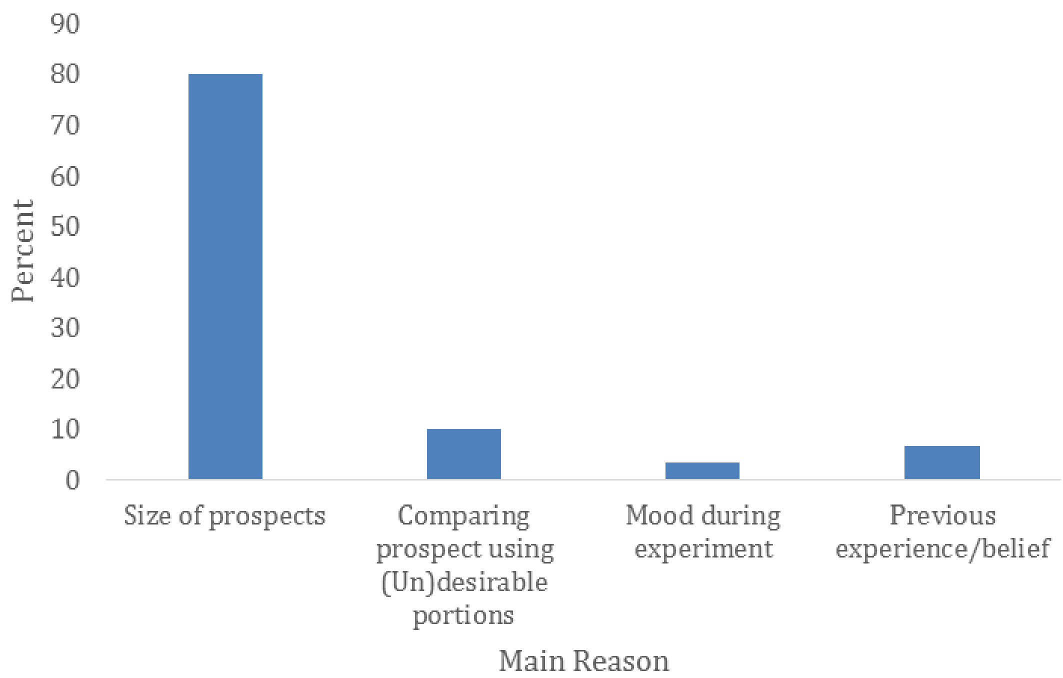


Figure 48. Participant reasons for choosing (or avoiding) a prospect

In addition, 10% said that they focused mainly on the portions that they desire in the gain domain (or dislike in the loss domain) suggesting that these group of participants inferred correspondence between the two prospects and possibly mapped values across prospect such that for every value in Prospect A there assumed an equivalent value in B.

In summary, the pilot experiment made it possible to identify ambiguous areas in the experiment. In addition, the pilot survey enabled the researcher estimate the resources and time required for each respondent to complete the experiment.