ESSAYS ON COMMUNICATION AND BEHAVIOUR UNDER RISK AND AMBIGUITY

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature: P. Marimo

Abstract

This dissertation consists of three chapters focusing on behaviour under risk and ambiguity. The first chapter analysed the best method to communicate risk information to weather forecast users whilst the last two analysed smallholder farmers' and students' decision making on crop selection when presented with uncertainty information of drought.

In the first chapter, experimental economics methods were used to assess forecast user understanding of information in temperature forecast. We tested whether undergraduate students presented with uncertainty information (90th percent confidence intervals) in a table and bar graph format were able to correctly understand the forecast and use the extra information to choose the "correct" (most probable) outcome than if they are presented with a deterministic forecast. Participants from the University of Exeter were asked to choose the most probable temperature outcome between a set of "lotteries" based on the temperature up to five days ahead. If they chose a true statement, participants were rewarded with a cash payment. Results indicate that on average participants provided with uncertainty information performed better than those without. Statistical analysis indicates a possible learning effect as the experiment progressed.

The second chapter assesses if there are gender differences in the behaviour of smallholder Zimbabwean farmers when faced with risk and ambiguity. The risk and ambiguity preferences of male and female farmers were elicited using a modified Holt and Laury (2002) field experiment. Farmers were asked to choose whether or not to adopt a new drought tolerant variety under different probabilities of a drought occurring. Subjects in one group were presented with known probabilities whilst another group was presented with ambiguous probabilities (range). Most of the farmers' exhibited extreme ambiguity and risk aversion and female farmers were more averse. Results indicate heterogeneity and the need to disaggregate samples when analysing research results as there maybe underlying factors affecting different groups.

The third chapter elicited the risk and ambiguity attitudes of vocational college students in Zimbabwe. Results indicate that in general, students were both risk averse and ambiguity averse. Those presented with the risk treatment were less

risk averse compared with those shown the ambiguity treatment. Participants who were presented with the ambiguity treatment behaved as *pessimists* and perhaps made decisions based on probability of drought that was higher than the provided centre of the range. We found gender differences in risk attitudes: contrary to the norm, female participants were less risk averse compared to their male counterparts. This is however when all subjects are pooled together. Results also indicate that a higher certain payoff perhaps incentivises consistency and increases risk aversion. The data seems to indicate anchoring effects from varying the order the probability of drought was presented.

Table of contents

List of tables

CHAPTER 1

CHAPTER 2

CHAPTER 3

List of figures

CHAPTER 1

CHAPTER 2

CHAPTER 3

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I dedicate this thesis to my family. You are and will always be close to my heart. Words can't explain how grateful I am.

INTRODUCTION

Risk and ambiguity are constantly present in almost every aspect of our lives. Given the inherent uncertainty in for example weather forecasts, climate change impacts, financial forecasts, health risks, food and so forth, it is fundamental that uncertainty information is communicated effectively. Providing uncertainty information has the potential to improve decision making, however for users to use the information efficiently in decision making, they must first understand and interpret it correctly. Presentation format is therefore critical as it affects the extent to which users can understand, interpret and use the information. The latter (interpretation and use) however also depends on other factors such as: preferences of the individuals, perceptions related to the risk in question, personal experiences, personal characteristics and source of information. Depending on the context, presentation format can induce different reactions. Given the details above, it is desirable that methods of presenting risk and ambiguous information are *objectively* evaluated. The diagram below shows a simple interaction of the issues discussed above. This is just a simple interpretation of the contents in this thesis but there are other complexities involved that are not shown in the diagram.

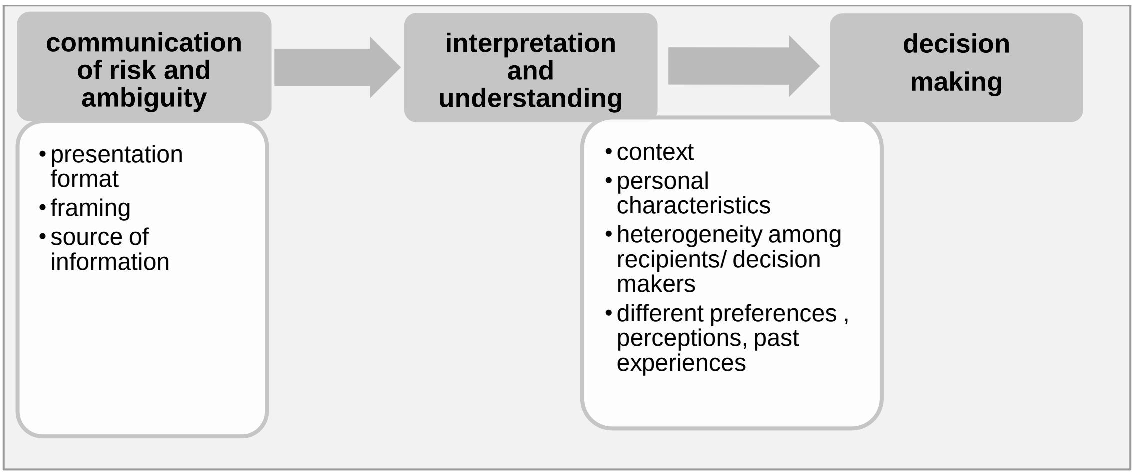

Fig 1: Illustration of thesis components

According to Libby and Lewis (1977) the decision making process involves three phases: input-process-output. The nature and format that information is presented influences the three phases thus affecting the decision. Various theories from a psychological, cognitive, normative and sociological perspective have been put forward to explain how presentation format affects decision making[1]. One suggestion is that the human brain has two different information processing systems: experiential and analytical. The former system is emotion driven and it adapts by empirically learning from experience; vivid images are associated with this system. This system controls the survival behaviour of individuals (CRED, 2009). The analytical system is related to logic and is used to process statistical information. The two systems are thought to operate in a parallel manner, however if there is a divergence in the output, the analytical system has less influence and behaviour is determined by the experiential system (Dietz and Bidwell 2012, pg 103). These systems can be used to understand the effect of probabilistic information in weather and climate change communication and thus help in product development (NRC 2006, Marx et al. 2007). Experiential processes however receive less attention and a better understanding of this system may help in producing improved risk communication products (Marx et al. 2007).

This dissertation is composed of three chapters on the impact of communicating risk and ambiguous information on individuals' behaviour using experimental economics techniques. The first chapter of the thesis, done in collaboration with the UK Met Office focused on communication and interpretation, whilst the second and third also included decision making. The former presents research on the best method of communicating uncertainty information in temperature forecasts. A bar graph and table format with uncertainty information is compared to a deterministic forecast using undergraduate students. Assessing how weather information is disseminated to users is useful. Including information on uncertainty better represents the capability of the forecasts and provides the potential for better decision making, but information has to be communicated effectively in a format that users can interpret, use efficiently and avoid poor decisions. The second and third chapters elicited the risk and ambiguity attitudes of male and female smallholder farmers and vocational students in Zimbabwe using different presentation formats; risk was presented as exact percentages and ambiguity was presented as a range of probabilities. Participants were asked to decide whether or not to adopt a drought tolerant crop variety under different risk levels. Understanding individual risk/ambiguity preferences in agriculture is important as it

[1] See Ghani et al (2009) for a summary.

affects economic decisions like technology choice, crop selection, crop insurance and so forth, for instance, crop selection is a choice over risk levels since some crops are more tolerant to variance in weather while others may be less tolerant. Risk and ambiguity preferences should therefore be considered in the policy making process especially regarding the poor in developing countries who rely on agriculture as a source of livelihood and food security.

The first chapter contributes to literature by comparing different presentation formats on temperature forecast interpretation and understanding. The study assesses if participants understood and could interpret uncertainty information (90^{th} percentile confidence interval) presented in a table and bar graph format. No studies were found that specifically tested these formats in meteorology. The performance of participants presented with uncertainty information was compared to those who were presented with a deterministic forecast to assess the value of providing the extra information. Participants were asked to choose the most probable temperature outcome between a set of "lotteries" based on a 5 day temperature forecast. If they chose a true statement, participants were rewarded with a cash payment. Results indicate that providing uncertainty information improves performance. Furthermore, results indicate a possible learning effect. Our findings can be used by the Met Office to help them decide which format to use to best disseminate weather information to the public and other partners, and to determine the value of presenting probabilistic information. Results also add to the knowledge on weather forecast interpretation and decision making when provided with uncertainty information presented in a bar graph or table format.

The second and third chapter assess actual decision making under risk and ambiguity using a modified Holt and Laury (2002) design. The former compared the risk and ambiguity attitudes of male and female smallholder farmers. Our experiment involved making a series of 10 choices from two options. Farmers were asked to choose whether or not to adopt a new drought tolerant crop variety after being told the exact probability of a drought occurring (e.g. 40% probability of drought) or the range (e.g. 20-60% probability of drought). The risk probability was equivalent to the middle of the range of the ambiguous lotteries. Adoption was the safe lottery whilst non-adoption was the riskier lottery. Participants were presented with *either* the exact probabilities (i.e. all the 10 decisions showed the exact probability) *or* the range of probabilities and not a mixture; hence there were two groups of participants. The experiment was slightly modified such that participants had to choose the risky option for the first few decisions before switching to the safe option. Our method of elicitation for ambiguity attitudes, which involves the use of imprecise probabilities (range of probabilities / probability intervals) in conjunction with a multiple price list, is non-existent in empirical studies on decision making in developing countries. This allows us to measure whether or not participants are optimistic or pessimistic decision makers. This study contributes to the risk and ambiguity preferences literature in that it measures both ambiguity and risk preferences of smallholder farmers from a gender perspective. Often, studies done in developing countries with farmers focus on one of the two, either ambiguity or risk aversion but not both and we found no studies that exclusively focused on gender differences. Results provide useful insights to help agricultural development planners and policy makers make more informed decisions regarding insurance policies, technology adoption initiatives and dissemination of weather, climate change or other agriculture related risk information.

In the third chapter, vocational students from colleges that specialise in agricultural courses were presented with the same decision criterion which was given to the farmers. However, the students' experiment involved two parts, each with 20 decisions. In the second part, the payoff for the safe option was increased such that the decision choice was between a sure bet and a lottery. In addition, the order in which the probability of drought was presented was randomised to assess potential anchoring effects. Only one study was found that used different orders in an MPL format for measuring risk preferences and none for ambiguity. This study fills the literature gap by providing results on the risk and ambiguity attitudes from African students' perspective who will in the near future be making farming decisions under uncertainty and offering advice to farmers. Results indicate framing and order effects on consistency and risk/ ambiguity preferences.

Farmers and vocational students in the second and third study perhaps used the experiential processing system which was discussed earlier to make their decisions. This is more so for the experienced farmers who chose to adopt a new drought tolerant variety even at the lowest probability level of the drought occurring. Past drought experiences coupled with the economic downturn over the past few years in Zimbabwe stored in the participants' memories therefore may explain their behaviour. As mentioned earlier, the experiential system controls the survival behaviour of individuals; hence in order to avoid starvation, participants chose the safe option (this is related to the safety first principle). This result reiterates the need to consider the experiential process when developing risk communication products. Framing the decision criterion as 'probability of drought' might also have influenced the results. Subsequent studies should perhaps include a control with a different framing that is less favourable.

In summary, this dissertation shows the importance of presentation format and framing on decision making. How information is presented induces different reaction patterns, preferences and consistency levels based on different individual characteristics and context. Development planners, policy makers and risk information providers should take this into consideration in order to reap rewards and ensure targeted individuals or groups make effective decisions.

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CHAPTER 1: Communication of uncertainty in temperature forecasts[2]

1.1. Introduction

Providing probabilistic weather information to users has the potential to improve decision making, since weather is uncertain due to the chaotic nature of the atmosphere. Accordingly, the National Research Council (NRC:NRC, 2006) states that a forecast is incomplete if uncertainty information is not included. The Met Office, through the use of ensemble forecasting and other techniques is capable of providing probabilistic estimates of weather forecasts. Studies that assess decision making when provided with probabilistic weather information have concluded that on average, participants who were given uncertainty information made significantly better decisions than those without (Roulston et al. 2006, Roulston and Kaplan 2009, Joslyn and LeClerc 2012, Nadav-Greenberg and Joslyn 2009). In addition to the benefit of improved decision making, the World Meteorological Organisation (WMO:WMO 2008) states that communicating uncertainty information also; promotes user confidence, helps manage user expectations and reflects the state of the science. Still questions arise on whether or not the presentation format makes a difference in interpretation and understanding. For uses to respond and use the information effectively in decision making, they must first understand and interpret it correctly.

Different presentation formats/designs can be used to illustrate the same data in various fields. However, the way that information is presented and consequently how we interpret or process it has the potential to influence decision-making. Winett and Kagel (1984) note that although messages might contain the same information, the *format* and *modality* of presentation: visual, auditory or kinaesthetic (see, Fleming and Mills 1992) and *context* in which the information is presented can have fairly different effects. Speier (2006) concluded that how information is presented and decision performance is moderated by the complexity of the task. The type and source of information can also factor into how recipients process uncertainty information, hence the need to specify the source when communicating hydromeorological forecasts (NRC 2006). Cognitive psychologists suggest that

[2] This chapter is collaborative work with Ken Mylne and Martin Sharpe from the UK Met Office and Professor Todd Kaplan (University of Exeter).

individuals process information based on two systems: experiential and analytic (Epstein 1994). The former is linked with past experiences and emotions whilst the later include logical reasoning and controls analysis of scientific information. These systems can be used to understand the effect of probabilistic information in weather and climate change communication and thus help in product development (NRC 2006, Marx et al. 2007, Shome et al. 2009). Experiential processes however receive less attention and a better understanding of this system may help in producing improved risk communication products (Marx et al. 2007).

The Met Office Public Weather Service (PWS) is constantly developing new products for disseminating weather information to users. After public consultation, they have a new format for presenting probabilistic forecast information for use on the Met office website. To make sure that the information is being communicated effectively to users in a way they understand and that will allow them to make better decisions it is desirable that methods of presenting the information are *objectively* evaluated. This study follows the same approach that was used by (Roulston and Kaplan 2009). Their study tested the ability of subjects to understand uncertainty information in a fan chart format. In our study, we test two different presentation formats; a table and graph format for expressing uncertainty in 5-day temperature forecasts. In addition, our study includes a comprehensive time analysis to assess if there is a possible learning effect between the formats and also tests for order effects by randomizing the order of how the questions were asked. Randomization assesses the speed with which participants' improve their use of uncertainty information. We used experimental economics lab techniques to assess if participants understood and could interpret uncertainty information presented in a table and bar graph format than if they are presented with a deterministic forecast. No studies were found that specifically tested these formats in meteorology and a review of studies that used other formats and their impacts on decision making are presented in Section 1.2.

The study will determine whether the method/format for communicating uncertainty information makes a difference on subject understanding of the forecast and test the speed at which subjects are able to learn with either method. The results of the study will be used by the Met Office to help them decide which format to use to best disseminate weather information to the public and to determine the value of presenting probabilistic information.

Initiatives on communicating forecast uncertainty

Various organisations emphasize the need to communicate uncertainty information in hydrometeorological forecasts and as such have taken initiatives to this effect. The American Meteorological Society (Hirschberg et al. 2011) recently published a strategic implementation plan for generating and communicating forecast uncertainty; the World Meteorological Organisation (WMO 2008) provides strategies on how best to communicate uncertainty; whilst the National Research Council (NRC, 2006) published a report with recommendations for effective communication and better decision making. One of the goals highlighted in the AMS' report is to: *"Communicate forecast uncertainty information effectively, and collaborate with users to assist them in interpreting and applying the information in their decision making".* Under this goal, one of the objectives (Obj. 2.4) which is closely related to our study is to: *"Improve the presentation of government supplied uncertainty forecast products and services."* Presentation format is fundamental as it determines whether or not users understand and can correctly decipher the information for use in decision making.

According to NRC (2006), '…understanding, communicating, and explaining uncertainty should be an integral and ongoing part of what forecasters do and are essential to delivering accurate and useful information.' The use of probabilistic forecasts can potentially increase the complexity of the information being transmitted to users and may lead to misinterpretation, hence the need to ensure that this information is communicated effectively. NRC (2006) and WMO (2008) provide suggestions on methods to communicate uncertainty information and reiterate the importance of taking into account the heterogeneity in the stakeholders that require and use forecasting information when developing information products to benefit users. NRC (2006) accentuate the need to incorporate the knowledge and expertise of various sectors (e.g. social and behavioural scientists) in product research and development which in turn can improve effectiveness and efficiency. This study is in collaboration with the UK Met Office and uses experimental economics to test forecast user understanding of different presentation formats.

1.2. Literature review

This section will review existing literature on communication of uncertainty in weather forecasts using probabilistic forecasts, methods used to present information, forecast user understanding and decision making when provided with probabilistic forecasts.

Understanding probabilistic forecasts

Uncertainty in hydrometeorological forecasts can be presented in various forms which include fan charts, bar graphs, tables, numerical data, images, maps, verbal descriptions, meteograms and so forth. Studies that have been conducted indicate that users prefer probabilistic rather than point forecasts (see., Baker, 1995; Morss et al., 2008).The format in which uncertainty information is presented has an impact on understanding which will in turn affect decision making. Handmer and Proudley (2007) note that non-specialists just require a functional understanding and not necessarily an in-depth awareness of probability theory to interpret probabilistic forecasts. These results are supported by (Patt 2001, Murphy et al. 1980). Patt (2001) used Zimbabwean smallholder farmers as subjects and concluded that farmers understood the probabilistic information on El Nino cycles and were able to make decisions using the provided information. Murphy et al (1980) found that most of the respondents in their sample understood and preferred the use of probabilities in precipitation forecasts. Misinterpretations of uncertainty information are mostly reported in public understanding of probability of precipitation forecasts (Gigerenzer et al., 2005 and Morss et al., 2008).

Gigerenzer et al. (2005) asked respondents from New York and Europe (Amsterdam, Athens, Berlin, Milan) what they understood by ‘30% chance of rain tomorrow’. The majority of the New York participants correctly understood the forecast and gave the meteorological interpretation (when the weather conditions are like today, in 3 out of 10 cases there will be (at least a trace of) rain the next day) whilst this was not the case for the Europeans (most indicated that it meant it would rain 30% of the time). They attributed this to the fact that the former had prior exposure to probabilistic precipitation forecast thus indicating user understanding perhaps improves with time. They also note that risk communication is improved if the class of events to which a single event probability refers is specified. Morss et al. (2008) also investigate understanding of probability of precipitation forecasts (PoPs) and unlike Gigerenzer et al. (2005) they find that the majority of US public in their sample could not give the meteorological interpretation. They conclude that understanding forecast uncertainty from a meteorological perspective is less important, what is more important is for users to understand the provided information 'well enough to infer information of interest to them that they can use in decisions'.

Joslyn and Nichols (2009) compared participants' responses to wind speed forecasts expressed as frequencies and probabilities. Uncertainty was presented as 90%, 9 times out of 10 or 90 out of 100% and a reference class was also included explaining how the forecast was derived (computer models prediction or similar atmospheric conditions). Results indicated that participants understood better information presented as probability rather than frequency. Savelli and Joslyn (2009) study the best way to communicate web based temperature forecasts using visualizations (bracket, plus/minus) and textual keys (verbal, probability, frequency). Participants were given a 2 day forecast and agricultural scenarios that involved protecting their crops from freezing conditions. The authors conclude that presentation format affects ease of forecast understanding and accuracy. Those provided with uncertainty visualisation had a better understanding of the amount of uncertainty compared to those without any visualisation. They also found that, the 'verbal only' and 'plus/minus' contexts were not the best methods as they were associated with increased errors.

Improved decision making with uncertainty/probabilistic information

The provision of uncertainty information has the potential to improve decision making. This section will highlight studies in hydrometeorology that support this notion. The UK Met office recently used a weather game to assess different presentation formats for rainfall and temperature forecasts which differed in style and complexity of information provided[3]. Participants were asked to make a decision and rate their confidence that it would rain or a certain temperature threshold would be met. Preliminary results indicated differences in the presentation format; age and education attainment also played a major role in

[3] http://www.metoffice.gov.uk/barometer/features/2012-04/playing-the-game-of-uncertainty
http://www.wmo.int/pages/prog/www/DPFS/Meetings/ET-EPS_Geneva2011/documents/MetOfficeKTNReport_Finalpub.pdf

participants' decision making. Results also showed that for straightforward decisions, providing uncertainty information did not confuse participants; on average, participants made better decisions in complex scenarios with uncertainty information and more detailed information on forecast uncertainty induced better decision making.

In Roulston et al. (2006), participants were given the role of managing a road maintenance company and had to decide whether or not to treat roads with salt to prevent icing. Failure to salt the roads and subsequent icing incurred a penalty equivalent to road usage demand the following morning. Three groups of participants were used: the first one was provided with a point forecast and average forecast error. In addition to the point forecast, the second was given the standard error and told that there was 'two thirds chance that actual overnight low would fall inside the range given by point forecast $\pm$ standard error' whilst the third group was explicitly told the probability that the temperature would be below freezing (32°F). Participants provided with standard error information performed better and had more expected profit and reduced their exposure to risk compared to those without. The additional information on probability of freezing provided to the third group did not have a significant impact.

Nadav-Greenberg and Joslyn (2009) and Joslyn and LeClerc (2012) replicated the (Roulston et al. 2006) study and included other conditions. In the former study, participants received either uncertainty information (probability of freezing) or deterministic forecasts (overnight low temperature) and made a series of decisions. Results indicated that participants who were provided with uncertainty information made better decisions and made less errors compared to those who had the deterministic forecast. Participants with probabilistic forecasts were less risk averse (chose to salt even in low probability ranges) and less risk seeking (salting more often in high probability ranges). In Joslyn and LeClerc (2012), various formats were tested; these included: deterministic forecast (expected night time low temperature), freeze frequency, probability of freezing and decision aid where advice was given (for example 'applying salt is recommended in these circumstances') and decision aid plus uncertainty. All the forecasts included the deterministic forecast. Results showed improved decision making with uncertainty and increased trust in the forecast. The combination of uncertainty and advice that acknowledged and quantified the uncertainty resulted in the best performance and significantly reduced errors. Participants with uncertainty information took appropriate precautions by acting when the weather was unfavourable and withholding action when it was unnecessary compared to those with just the deterministic forecast.

Nadav-Greenberg, Joslyn and Taing (2008) used experts (professional forecasters) and non-experts as subjects to investigate the effect of visualizations on the understanding and use of wind speed forecast uncertainty. They tested 3 formats; a chart with uncertainty information, chart showing worst case scenario, a box plot of likely wind speeds and combinations of these. The task was, '…to determine the relative uncertainty in the forecast, predict wind speed, and decide whether to post a high-wind warning advisory'. There was no difference in the behaviour of non-experts and professional forecasters. Their results indicated that, box plots enhanced reading accuracy, the chart with uncertainty information improved the degree of awareness, the chart with the worst case scenario introduced bias in the deterministic forecast and an interactive display might be the best format.

Roulston and Kaplan (2009) used fan chats to test whether or not including uncertainty information improved forecast understanding and whether or not participants could choose the most likely criterion given a five day temperature forecast . Information was presented as either fan charts with just the expected temperature or fan charts with the expected temperature plus uncertainty information (50% and 90% confidence intervals). Participants with uncertainty information were more likely to choose the most probable outcome and this was irrespective of the gender or subject of study.

Graphical versus tabular presentation of information

Our research compares graphical and tabular presentation of temperature forecast uncertainty. Very few studies were found that compared the two formats in meteorology. Stephens, Edwards and Demeritt (2012) note that, not much research has been published on how best to visualise probabilistic weather products. This section highlights studies that rate tabular and graphical aids. Most of the studies that were found are in accounting or management (see., So and

Smith 2003, Sullivan 1988, Cardinaels 2008, Anderson and Mueller 2005, Ghani et al. 2009). NRC (2006) reports that the graphics used to convey monthly and seasonal forecasts by the *Climate Prediction Center (CPC) were* difficult to understand for many users and recommend the use of both graphical and tabular formats*.* They also recommend that the forecast should include full exceedence probability distributions of the probable monthly and seasonal temperature and precipitation; and more research on these formats.

In some studies, participants rate tabular reports as being less complex than graphical reports (Lusk and Kersnick 1979, Dickson, DeSanctis and McBride 1986, Vessey and Galletta 1991) whilst others prefer graphs to tables (Zmud 1978). However when actual experiments are done, there are inconsistencies on which format is better. In some instances there are no differences in performance between subjects presented with tabular and graphical data (Benbasat and Dexter 1985). In Remus (1984), both participants made costly decisions in the production scheduling problem whether or not they were provided with tabular or graphical displays. However when the erratic components of the decisions were reduced, the tabular aids outperformed the graphical aids.

In other studies, graphical displays do better than tabular displays for example in an assessment of risk avoidance, participants who were shown graphical displays were willing to pay a higher price for improved toothpaste or set of four improved tires. These participants were also more willing to recommend others to buy improved tires compared to those who were shown numerical displays (Chua, Yates and Shah 2006). Results from a study on communication of investment risk to consumers concluded that, presenting relative investment performance and probability of losing money in a bar chart instead of a table reduces customer's ability to correctly answer questions by between 50-75% (Driver et al. 2010). This study will examine two methods of communicating uncertainty information in temperature forecasts, specifically whether or not lay users can understand and interpret uncertainty information presented in a table or bar graph format compared to a deterministic forecast.

1.3. Experimental design

A total of 230 undergraduate students from various disciplines at the University of Exeter were recruited to participate in the experimental sessions. The sessions were computer based and took place in the Finance and Economics Experimental Laboratory (FEELE) at the University of Exeter. Participants were presented with a sequence of 20 "lotteries" or rounds in which they had to choose the most probable temperature outcome based on a 5-day forecast. Each lottery consisted of two statements and if a true statement was chosen, participants were rewarded with £0.50[4]. The two statements in each lottery had the following structure:

Statement A: The maximum temperature on Day D1 is above/below X deg. C
Statement B: The maximum temperature on Day D2 is above/below Y deg. C.

For each lottery, both the statements had the same preposition: both stated that the maximum temperature was "above" or both were "below" X/Y deg. C and none of them were "mixed" (i.e. one statement above and the other one below). Participants were divided into three treatment groups: A, B and C. The 5-day temperature forecast information was presented as follows:
Group A: Table with a point forecast
Group B: Table with point forecast and uncertainty information
Group C: Bar graph with point forecast and uncertainty information
The uncertainty information that was provided for groups B and C showed the temperature range within the 90% confidence interval. The Group C format was at the time of the experiment under trial on the Met Office website. Figures 1.1 and 1.2 show examples of two lotteries presented to the three groups.

The same graphs were shown for all the participants in a particular group but in different orders. Four random question orders were used[5]. The randomisation of the orders was done in order to test speed of learning differences between the different presentation formats as it allowed us to distinguish between changes in

[4]Experimental economics normally uses monetary incentives in order to induce individuals' preferences. Payments based on performance helps to disentangle issues of what their preferences are and how well they can use the information provided to follow these preferences. Financial incentives are therefore a tool to control the preferences of participants. Real incentives have been shown to induce more 'rational' behaviour compared to hypothetical scenarios (Davis and Holt, 1993). Future studies can perhaps also ascertain to what extend the monetary incentive is considered important by respondents.
[5] The question orders were: order 1 (1, 2,..., 20); order 2 (20, 19,..., 1); order 3(11, 12,..., 20, 1, 2,..., 10); order 4(10, 9,..., 1, 20, 19,..., 11). The question types (class) associated with the orders are shown in Table 1.6

difficulty and changes in timing. For instance if question 4 had a lower number of correct answers than say question 17, it could be because question 17 is an easier question or that question 17 just happened to come later in the sequence of questions. By also having an order where question 17 came before question 4, we can then estimate both a learning effect and a difficulty level.

(a)

	Maximum Temperature (°C)				
Most likely	5	6	5	1	3
	Sat 1 Jan	Sun 2 Jan	Mon 3 Jan	Tue 4 Jan	Wed 5 Jan

(b)

	Maximum Temperature (°C)				
High range	6	10	14	3	11
Most likely	5	6	5	1	3
Low range	3	2	1	-1	-1
	Sat 1 Jan	Sun 2 Jan	Mon 3 Jan	Tue 4 Jan	Wed 5 Jan

Product description

Table shows temperature ranges for a five day forecast. Temperatures fall within the indicated range roughly 9 out of 10 times with the most likely temperature in the middle. Presentation format is to help the Met Office develop and improve a product.

c)

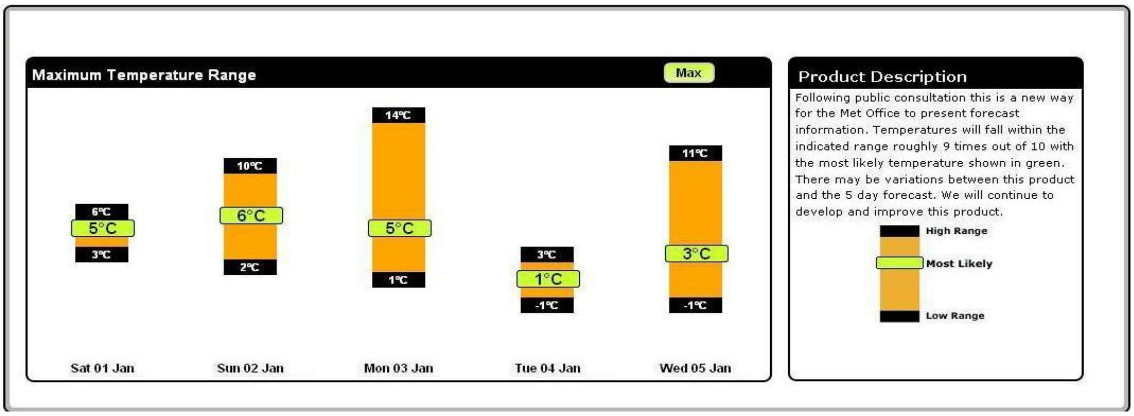


Figure 1.1: Forecasts presented to groups A, B and C in question 1 of the experiment

The participants were given the option to choose between two statements and receive £0.50.

Statement A – The maximum temperature Monday is above 6 deg. C OR

Statement B – The maximum temperature on Tuesday is above 0 deg. C

(a) The forecast presented to group A in question 1 of the experiment.

(b) The forecast presented to group B in question 1 of the experiment.

(c) The forecast presented to group C in question 1 of the experiment.

(a)

	Maximum Temperature (°C)				
Most likely	4	4	5	5	6
	Sat 22 Jan	Sun 23 Jan	Mon 24 Jan	Tue 25 Jan	Wed 26 Jan

(b)

	Maximum Temperature (°C)				
High range	6	10	10	8	14
Most likely	4	4	5	5	6
Low range	3	2	2	2	0
	Sat 22 Jan	Sun 23 Jan	Mon 24 Jan	Tue 25 Jan	Wed 26 Jan

Product description
Table shows temperature ranges for a five day forecast. Temperatures fall within the indicated range roughly 9 out of 10 times with the most likely temperature in the middle. Presentation format is to help the Met Office develop and improve a product.

(c)

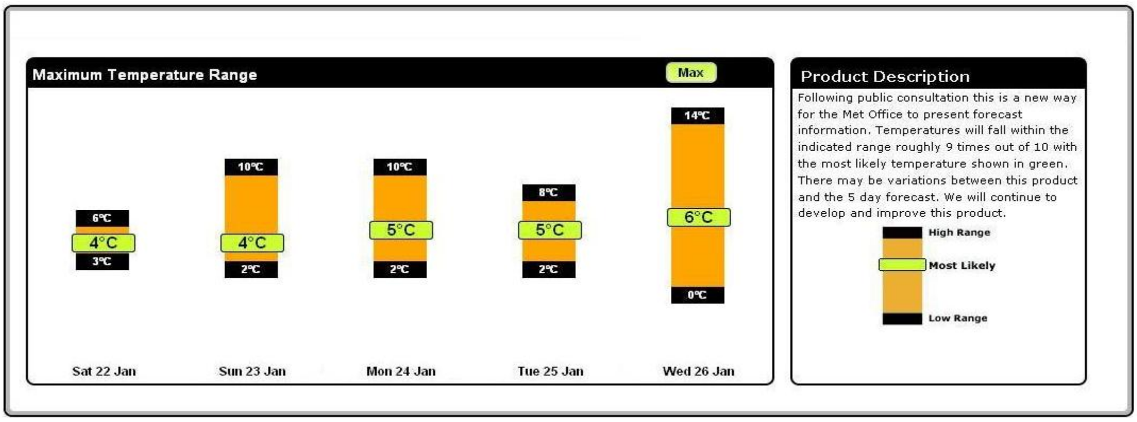


Figure 1.2: Forecasts presented to groups A, B and C in question 4 of the experiment

The participants were given the option to choose between two statements and receive £0.50.

Statement A – The maximum temperature on Saturday is above 5 deg. C OR

Statement B – The maximum temperature on Wednesday is above 8 deg. C

(a) The forecast presented to group A in question 4 of the experiment.

(b) The forecast presented to group B in question 4 of the experiment.

(c) The forecast presented to group C in question 4 of the experiment.

Instructions (shown in Appendix 1.1) were provided on the computer screens and to assess whether or not participants could read the graphs and tables they had to answer three test questions[6] at the beginning of the experiment. After every lottery,

[6] Test questions were not incentivised and were included in the experiment so that participants could familiarise themselves with the presentation formats. Answering them correctly or not was not expected to influence their interpretation and choice of answers for the 20 lotteries as they were not related in any way. We therefore framed and worded the questions differently. A dummy is included in the probit regression analysis to test if they had any effect.

participants were shown a computer screen with the results from that particular lottery. This contained information on which statement the participant chose, which of the statement was true or false, the actual temperature for each day and their cumulative payoff.

1.4. Data

The temperatures that were used in the experiments were not actual forecasts; rather the temperatures were generated using synthetic means.[7] The 'observations' (answers/"actual" temperatures for each day) were produced using the triangular distribution with the peak at the stated "most likely" value and the tails beyond the stated "High range" and "Low range", to account for the 1/10 probability of observations falling outside the forecast range. The triangular distribution is a continuous probability distribution used when there is limited sample data or when the underlying probability is unknown (Kotz 2004). It has three parameters; minimum, maximum and the mode/most likely value. The distribution is used in project management (e.g., Larham 2010, Back, Boles and Fry 1999), risk analysis (Johnson 1997) and business decision making. The distribution is defined on the range $x \in [a,c]$ with the probability density function:[8]

$$f(x) = \begin{cases} \dfrac{2(x-a)}{(b-a)(c-a)} & \text{for} \quad a \le x \le b \\ \dfrac{2(c-x)}{(c-a)(c-b)} & \text{for} \quad b < x \le c \end{cases} \tag{1}$$

And cumulative distribution functions:

$$F(x) = \begin{cases} \dfrac{(x-a)^2}{(b-a)(c-a)} & \text{for} \quad a \le x \le b \\ 1 - \dfrac{(b-x)^2}{(b-a)(b-c)} & \text{for} \quad b < x \le c \end{cases} \tag{2}$$

Where $b \in [a,c]$ = mode or most likely, a = minimum value, c = maximum value

[7] The initial plan was to use the (Roulston and Kaplan, 2009) study as a control to check stability of results and also to test the new design in comparison to the fan chats in that study. Data used in this study was also synthetically generated but extracting the data for just the maximum temperature (for use in our study) was complex. We therefore ended up using data synthetically generated by the Met Office using the triangular distribution as we did not have actual forecast distributions.

[8] Evans, M., Hastings, N. and Peacock, B., 2000. Statistical Distributions. Wiley-Interscience. New York. pg 187-188, New York.

A diagram illustrating the PDF of the triangular distribtion is shown in Figure 1.3. [9]

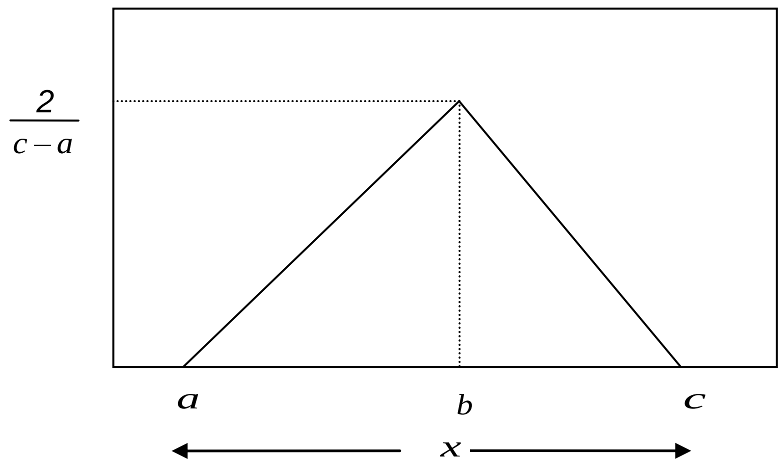


Figure 1.3: Illustration of the triangular distribution probability density function[10]

The questions were classified as easy, hard or swing. There were eight easy questions and the remaining were equally divided between hard and swing. The classification of the questions was done to give participants different real scenarios that forecast users would encounter on the Met Office website. Definitions of the question types are discussed below.

In order to define an easy question, a simple rule of the thumb would generate the correct answer. This rule of thumb did not require uncertainty information nor a difficult computation to choose the correct answer (hence the classification as *easy*). Specifically:

Easy – A hypothetical participant faced with the options where one statement is <= (or <) mode and the other > (or >=) mode, would always get the correct answer if one assumed mode=median.

More specifically, the "correct" choice is:

If the statements are "above" and in A the threshold temperature is > (>=) the forecast mode and in B it is < (<=) the mode, the choice is B: where A and B denote the statements A and B respectively.

If the statements are "above" and in A the threshold temperature is <= (<) the

[9] The triangular distribution does not assume mode=median. This assumption may not always be true for real forecast distributions, but in some instances, it affects how participants might have interpreted the uncertainty information. Information about the probability distribution was not specified to the participants. The experiment was a simulation of how the Met Office would present the real forecast on their website which does not provide information about the probability distribution. Providing the extra information about the probability distribution may potentially confuse participants especially if they are not aware of the triangular distribution. Experiments in which the distribution is specified can be a subject for further study.

[10] see Hesse, R. (2000) In The Classroom. Triangle Distribution: Mathematica Link for Excel. *Decision Line* 31.

forecast mode and in B it is > (>=) the mode, the choice is A.
If the statements are “below” and in A the threshold temperature is > (>=) the forecast mode and in B it is <= (<) the mode, the choice is A.
If the statements are “below” and in A the threshold temperature is <= (<) the forecast mode and in B it is > (>=) the mode, the choice is B.
For example question 1 (Figure 1.1 (a), (b) and (c)):
Statement A – The maximum temperature on Monday is **above** 6 deg. C
Statement B – The maximum temperature on Tuesday is **above** 0 deg. C
The mode for Monday is 5 deg. C and the mode for Tuesday is 1 deg. C, hence statement A > mode and statement B < mode therefore, if one assumes mode=median, the “correct”/most probable choice is B.

Swing– A hypothetical participant with just the point forecast assuming mode=median and same uncertainty at all forecasts (takes the distance from the point forecast as same deviation) would result in that participant choosing a different option compared to those with uncertainty information. For these questions, uncertainty information allowed you to make a better decision than if presented with the deterministic forecast. Question 4 in Figure 1.2 was a swing question. There is need to note that we do acknowledge that not all participants will assume the same uncertainty for all forecasts. Studies that have been done indicate that weather forecast users do understand that there is uncertainty in the point forecast which increases with longer lead time (Morss et al. 2008, Joslyn and Savelli 2010). In this study we will however assume the above and perhaps future experiments can measure ex-ante and ex-post the degree to which participants presented with a point forecast infer uncertainty at different lead times. Morss et al. (2008) reports that respondents had more confidence in shorter lead time temperature forecasts.

Hard– These questions cannot be classified as either easy or swing according to the definitions above. There were no prior assumptions about the mode or median which would lead to choosing the ‘correct’ answer.

At the end of the experiments, participants were asked to fill out a brief questionnaire (Appendix 1.2) and were then paid their total earnings in addition to a show up fee of £3. Most of the participants (51.3%) were from the business school whilst 35.2% were from humanities, the rest were science/engineering majors. The average age was 20.3 years (s.d= 2.7) and ranged between 17.9 and

45.2 years. Slightly more than half (52.6%) were female. Around 70% of the participants reported that English was their first language. All the instructions and questions were in English. Almost all the participants reported that one of their sources of weather information was the internet. Participants were also asked a basic question on the probability of a six appearing if a fair die was rolled twice; around 73.5% answered it correctly. Tables 1.1 and 1.2 give summary statistics.

Table 1.1: Number of participants by school, format and order

	Order	Business	Humanities	Sciences	Total
Format A	1	14	6	8	28
	2	9	6	8	23
	3	9	5	8	22
	4	3	4	7	14
Total		**35**	**21**	**31**	**87**
Format B	1	5	5	-	10
	2	5	5	-	10
	3	4	5	-	9
	4	5	4	-	9
Total		**19**	**19**		**38**
Format C	1	21	11	-	32
	2	19	11	-	30
	3	13	9	-	22
	4	11	10	-	21
Total		**64**	**41**		**105**

Table 1.2: Summary statistics

		% (n=230)
Race	European-British, American	69.1
	European-Other	12.6
	Asian/African	18.3
Year of study	1	50.9
	2	33.0
	3	12.6
	4	3.5
Source of weather information	Internet	93.9
	TV	59.6
	Radio	12.6
	Newspaper	13.1
	Ask someone	33.9
Frequency of checking weather forecast	Never/Hardly	30.0
	Weekly	24.8
	Every 2 or 3 days	26.5
	Daily	15.7
	More than once per day	3.0
English first language (yes)		70.0
Probability question (% correct)		73.5

1.5. Results

Result 1: Participants with uncertainty information performed better than those without; they correctly understood the forecast and used the information to choose the "correct" outcome. The "correct" answer was the more probable of the two statements that the participants were given as options.

Average earnings: The average earnings for the three groups are summarised in Table 1.3. Participants who were provided with uncertainty information (Groups B and C) earned more than those who did not have the extra information (Group A). A one way ANOVA showed that there was a significant difference in average earnings between the 3 groups: F (2,230) = 40.5, p<0.001. Post-hoc comparisons using the Tukey HSD indicated that Groups B and C had significantly higher earnings.

Table 1.3: Number of participants by treatment group and average earnings

	Number of participants	**Average earnings**[1]	**Std dev**
Group A	87	£6.33	0.61
Group B	38	£7.28	1.02
Group C	105	£7.45	1.00

[1]these were average earnings not including the £3 show up fee

Proportion choosing the correct outcome: On average, participants who were provided with Format B or C outperformed those with Format A regardless of the gender of participant, school or order in which the questions were presented except for the non-swing questions (Table 1.4). Since 70% of the questions were non-swing, most participants without uncertainty information answered them correctly.

Table 1.4: Proportion choosing correct outcome

	Format A		**Format B**		**Format C**	
	% correct	s.d	% correct	s.d	% correct	s.d
Humanities	66.4	47.3	76.1	42.7	74.3	43.7
Business	64.9	47.8	79.5	40.4	75.6	43.0
Sciences	67.6	46.8	-		-	
Female	64.9	47.8	79.8	40.2	72.9	44.5
Male	67.6	46.8	75.6	43.0	77.7	41.7
English first language	67.4	48.4	75.9	39.6	76.1	44.5
English not first language	62.6	46.9	80.7	42.8	72.9	42.7
Swing questions	18.0	33.8	60.5	35.6	59.7	38.7
Non swing questions	86.9	38.5	85.2	49.0	81.7	49.1
Order 1	66.6	47.2	80.5	39.7	75.0	43.3
Order 2	67.4	46.9	84.0	36.8	78.0	41.5
Order 3	62.1	48.6	68.3	46.6	75.5	43.1
Order 4	70.0	45.9	77.2	42.1	70.7	45.6
Overall	66.2	47.3	77.8	41.6	75.1	43.3

The difference in the proportion choosing the correct outcome between Group A and either Group B or C is greatest for the swing questions: (42.5% for B and 41.7% for C). Overall, on average participants chose the most probable outcome approximately 66.2%, 77.8% and 75.1% of the time for Groups A, B and C respectively. A one way analysis of variance (ANOVA) on the average number of correct choices from the 20 lotteries indicates significant differences between the formats at $p<0.05$: F (2, 230) = 20.6, $p<0.001$. Post-hoc comparisons using the Tukey HSD showed the average number of correct choices was significantly higher for participants presented with uncertainty information compared to those without. There were no significant differences between Groups B and C. The results are the same if analysis is conducted for the swing questions: F (2, 230) = 128.5, $p<0.001$ and non-swing questions: F (2, 230) = 3.5, $p<0.05$. For the orders, there are significant differences: F (3, 230) = 2.8, $p<0.05$.Post hoc indicates significant differences between orders 2 and 3, with higher number of correct answers for the former.

Analysis of cross effects: We also conduct ANOVAs to check for cross effects at $p<0.05$. Two way analyses of variance between format and different factors (school department, gender and English as first language) showed a significant effect for format. None of the individual factors had a significant effect except gender; male participants significantly chose more correct answers: F (1,230) = 11.4, $p<0.001$, when the independent factors were format and male. An ANOVA with format, male and school and their interactions as independent variables also had a significant effect for gender: F (1,230) = 7.4, $p<0.05$. There was no significant interaction between any of the factors The rest of the ANOVA results are in Appendix 1.3

Proportion who answered each question correctly. Table 1.5 summarises the percentage of participants who answered each question correctly, type of question, probability of statement A or B being correct and which statement was actually true. For all the swing questions, those with uncertainty information did better than those without.

Table 1.5: Summary showing the percentage of participants who answered each question correctly

Question	Format A	Format B	Format C	Chi^2	p	Probability		Actual	Class	Early correct[11]
	% Correct	% Correct	% Correct			Statement A	Statement B			N= no, Y=yes
1	97.7	73.7	62.9	33.9	0.000	0.56	0.78	1	easy	N
2	92.0	86.8	89.5	0.8	0.665	0.05	0.55	2	easy	N
3	9.2	44.7	23.8	20.1	0.000	0.78	0.69	both	swing	Y
4	19.5	78.9	73.3	66.9	0.000	0.26	0.38	2	swing	N
5	62.1	92.1	87.6	23.4	0.000	0.75	0.40	1	easy	Y
6	4.6	65.8	59.1	72.1	0.000	0.30	0.38	2	swing	N
7	92.0	89.5	89.5	0.4	0.830	0.78	0.92	both	hard	N
8	88.5	78.9	74.3	6.2	0.046	0.39	0.22	1	easy	Y
9	82.8	89.5	72.4	6.1	0.049	0.87	0.61	1	hard	Y
10	88.5	84.2	87.6	0.5	0.798	0.19	0.64	2	easy	N
11	34.5	44.7	71.4	27.3	0.000	0.19	0.30	2	swing	N
12	80.5	68.4	49.5	20.2	0.000	0.58	0.49	2	easy	Y
13	85.1	81.6	76.2	2.4	0.299	0.58	0.38	2	easy	Y
14	89.7	89.5	91.4	0.2	0.895	0.70	0.89	both	hard	N
15	89.7	81.6	90.5	2.3	0.312	0.95	0.57	1	hard	Y
16	25.3	73.7	85.7	76.1	0.000	0.05	0.19	neither	swing	N
17	80.5	81.6	85.7	1.0	0.606	0.60	0.78	2	hard	N
18	95.4	97.4	91.4	2.3	0.322	0.47	0.84	2	hard	N
19	92.0	97.4	95.2	1.7	0.419	0.50	0.78	2	easy	N
20	14.9	55.3	44.8	26.6	0.000	0.86	0.72	both	swing	Y

[11] Means the statement with the earlier date was the most probable outcome: for example if in a lottery the statements were for Wednesday and Friday, the former would be the most probable outcome. Variable was included to measure whether or not participants would be inclined to choose the earlier option as the lead time would be shorter for that option. If a participant always chose the earlier option, he/she would have a success rate of 40%.

Determinants of choosing the most probable outcome - Probit regression

Statistical analysis using a probit regression model estimated the determinants of choosing the most probable outcome. In our study, we were interested in the factors (predictors) that determine whether or not a participant chose the 'correct' (most likely) outcome. In order to do this a probit regression model was used. There were two possible outcomes (participant chooses the 'correct' / most likely outcome OR participant chooses a 'wrong' outcome). Hence the dependent variable (y) is binary i.e. y=1 if participant chooses the most likely outcome and y=0 otherwise. Some of the predictor variables (x) were, whether or not a participant was provided with uncertainty information (i.e. Format A, B or C), gender of the participant, whether or not the question was swing, how often they check the weather and so forth. The objective of using a probit model was to find the best fitting model to describe the relationship between the dependent variable and the predictor variables. This model was chosen instead of the conventional ordinary least squares (OLS) because of our binary dependent variable. Hence, the probability that a participant would choose the most likely outcome given a set of predictor variables is given by: $\Pr(y=1|x)=F=\phi(x\beta)$, where ϕ is cumulative distribution function of the standard normal distribution, x is a set of explanatory variables and β are parameters to be estimated .

The results of fitting a probit model to the data shows the relationship between the dependent variable (whether or not a participant would choose the most likely outcome) and the predictor variables but not the magnitude of the negative/positive effects and the β parameters cannot be directly interpreted hence marginal effects were computed. Marginal effects (ME) are evaluated by taking the derivative of the probability of choosing the probable outcome associated with a certain predictor (dF/dx). Results are presented in Table 1.6. All the predictor variables were binary variables (take values 0 or 1) except for 'response time' and 'round number'. The interpretation for the ME for the dummy variables would be the difference in the predicted probabilities of $x_i = 1$ and $x_i = 0$, holding all the other predictor variables constant at some value. A description of the variables used in the analyses is given in Appendix 1.4.

Table 1.6: Marginal affects results from probit regression model

	(1)	(2)	(3)	(4)
Round number	0.0005	0.0005	0.0005	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
Swing question	-0.379***	-0.474***	-0.292***	-0.292***
	(0.017)	(0.020)	(0.029)	(0.029)
Hard question	0.082***	0.005	0.030	0.030
	(0.016)	(0.020)	(0.020)	(0.020)
Male	0.030**	0.025*	0.026*	0.031**
	(0.014)	(0.014)	(0.015)	(0.015)
Age	-0.006**	-0.005**	-0.006**	-0.005**
	(0.002)	(0.00)	(0.002)	(0.002)
English	0.010	0.012	0.012	0.017
	(0.018)	(0.018)	(0.019)	(0.019)
Humanities	-0.037	-0.027	-0.033	-0.034
	(0.025)	(0.025)	(0.028)	(0.028)
Business	-0.024	-0.024	-0.031	-0.030
	(0.025)	(0.025)	(0.027)	(0.027)
Checks internet for weather forecast	0.023	0.038	0.036	0.036
	(0.031)	(0.033)	(0.033)	(0.033)
Checks weather every 2-3 days or less	-0.020	-0.022	-0.022	-0.021
	(0.015)	(0.015)	(0.015)	(0.015)
Format B	0.115***	0.136***	0.005	0.007
	(0.025)	(0.024)	(0.038)	(0.038)
Format C	0.103***	0.154***	0.007	0.003
	(0.018)	(0.018)	(0.024)	(0.024)
Probability question mistake		-0.043**	-0.046***	-0.047***
		(0.017)	(0.018)	(0.018)
Early correct		-0.141***	-0.153***	-0.153***
		(0.015)	(0.015)	(0.015)
Above		-0.063***	-0.079***	-0.079***
		(0.014)	(0.015)	(0.015)
Length		-0.213***	-0.102*	-0.103*
		(0.059)	(0.058)	(0.058)
Area		-0.331***	-0.217***	-0.217***
		(0.037)	(0.038)	(0.038)
Test question dummy		0.006	0.011	0.012
		(0.022)	(0.023)	(0.022)
Swing & Format A			-0.447***	-0.450***
			(0.039)	(0.039)
Swing & Format B			-0.005	-0.008
			(0.044)	(0.04)
Order 1				-0.006
				(0.021)
Order 2				0.017
				(0.021)
Order 3				-0.058**
				(0.023)
Area under ROC[12]	0.753	0.796	0.802	0.809
	(0.009)	(0.008)	(0.008)	(0.008)
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1				

Result 2: Further analysis using probit regression model indicates that participants who were provided with uncertainty information were more likely to choose the most probable outcome compared to those who were shown the table without uncertainty information

[12] To measure model fit, we used a Receiver Operating Characteristic (ROC) curve which shows how sensitivity varies with changing specificity. The dependent variable as mentioned before is binary (=1 if the participant chooses a 'correct' outcome and 0 otherwise). The vertical axis captures sensitivity which is the probability of correctly predicting a one (ratio of observations for which the estimated and actual values of yi equal one) whist specificity is the probability of correctly predicting a zero. The 45 degree line shows the trade-off between correctly predicting a one against the probability of correctly predicting a zero for a model without any predictive power. The larger the area under the curve (AUC), the better the model. An AUC of 1 therefore indicates perfect prediction. The AUC for our models are > 0.75, hence the models have predictive skill.

‘Swing question’, ‘Swing question & Format A’, ‘Format B’ and ‘Format C’ were significant determinants of choosing the most likely outcome at the 1% level (Table 1.6). The latter two variables have a positive effect indicating that participants shown uncertainty information were more likely to choose the correct outcome compared to those without. In model (2), Format B and C participants were on average 13.6 and 15.4% more likely to choose the correct outcome compared to Format A respectively. When interaction terms between the Format and ‘swing’ are added to the model, both Format B and C becomes insignificant but still have a positive impact (models 3 and 4). This means that on non-swing questions, there is no significant improvement by giving the participant uncertainty information. If a question was a swing question, the probability of participants picking up the most probable outcome was reduced by 29.2% on average; for participants who did not have uncertainty information (Format A), the probability of them choosing the correct outcome was reduced by a further 44.7%. This result is consistent with Roulston and Kaplan (2009), where the probability of choosing the correct outcome was reduced by 15.9% if the question was swing; with a further reduction of 47.7% for participants without uncertainty information on average.

Result 3: For some of the questions, providing uncertainty information may have been damaging- it reduced probability of choosing the most probable outcome

For some of the easy questions, participants who were provided with uncertainty information were less likely to choose the correct outcome compared to those without. We hypothesize that this would happen if the difference in the range between the asked and high/low range was higher in the ‘incorrect statement’ perhaps leading to *confusion* for participants with uncertainty information. The bigger range would not necessarily mean that this was the most probable outcome. For example in question 1 (Figure 1.1), which is an easy question, 26.3 and 37.1% of Formats B and C participants respectively, chose statement A as the most likely outcome: we posit that this might be because of the large area above 6 deg. C on Monday, but the most probable outcome would be statement B. This was also the case in questions 12 and 13. We test this using the binary variables ‘length’ and ‘area’ in the model where the former measured the effect for Format B participants and the latter Formats C. Area /Length equal one if statement with the higher range between the asked and low/high range was the incorrect statement for easy questions and 0 otherwise.[13] These variables therefore measured the magnitude of the probability of choosing the correct answer in these questions and are statistically significant in all models (Table 1.5). Providing uncertainty information for questions 1, 12 and 13 may have reduced the likelihood of choosing the correct outcome by 10.2% and 21.7% (model 3) for Format B and C participants respectively. We however cannot say definitively the reason why they did not choose the correct outcome is because of the large range; the reason why this may be occurring can be a subject for future research.

Result 4: Participants were more inclined to choose the option with the later date

This result is consistent with the Roulston and Kaplan 2009 study. Participants were more inclined towards choosing the option with the later date (i.e. statement B). 'Early correct' means that the predictor was equal to one if the option with the earlier date (e.g. Wednesday) was the most likely as opposed to the later one (e.g. Friday). Participants were on average, 15.3% less likely to choose the correct outcome if the option with the earlier date was the most likely (models 3 and 4). In Roulston and Kaplan (2009), participants were 11.9% less likely to do so. We would expect participants to choose the correct option if the date was earlier since there is a shorter lead time. However, our experiment only included a five day forecast; a forecast with longer lead time e.g. 14 days would perhaps produce different results.

Other probit results

'Age' has a negative effect on probability of choosing the most probable outcome, indicating older participants were less likely to do so; however the effect is relatively small. On average, male participants were more likely to choose the most

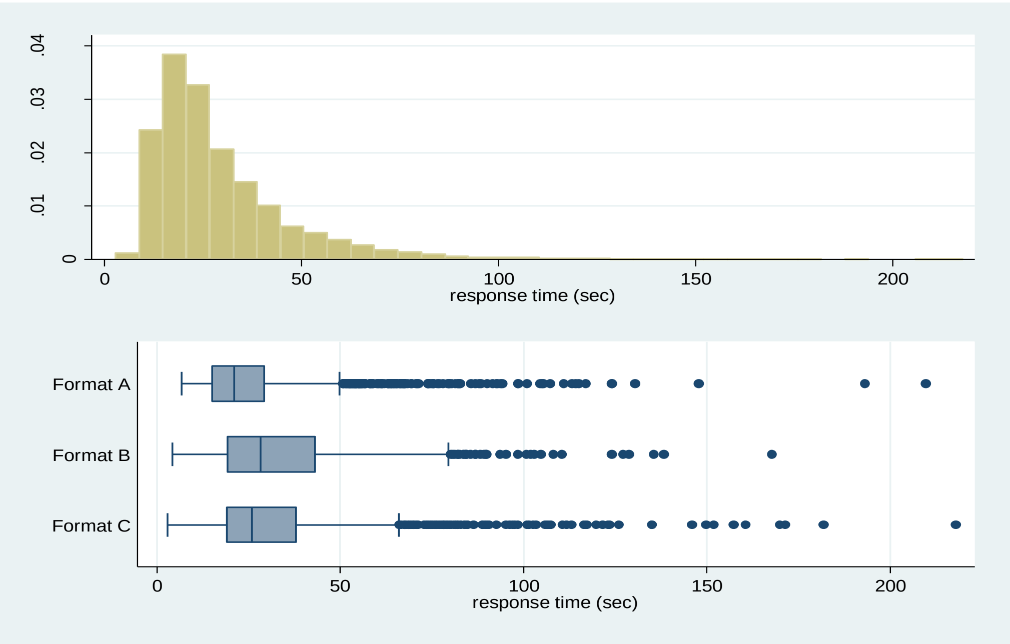
[13] More precisely, let :
H_A = high range on statement A , H_B = high range on statement B, L_A = low range on statement A , L_B = low range on statement B, x = asked temperature in statement A , y = asked temperature in statement A
Such that for example:
If statements were above, **area** =1 if question =easy, $H_A - x > H_B - y$, correct answer = B and participant was shown Format C; 0 otherwise
If statements were below, **area** =1 if question =easy, $x - L_A > y - L_B$ and correct answer = B and participant was shown Format C; 0 otherwise
If statements were above, **length** =1 if question =easy, $H_B - y > H_A - x$, correct answer =A and participant was shown Format B; 0 otherwise
If statements were below, **length** =1 if question =easy, $y - L_B > x - L_A$, correct answer = A and participant was shown Format B; 0 otherwise

likely outcome compared to their female counterparts. When the statements asked for the maximum temperature *above* X deg. C instead of *below*, it reduced the probability of the participants choosing the most probable outcome. When we controlled for order effects (model 4), results show order 3 participants were less likely to choose the most probable outcome compared to the other orders. The variable 'question number' was included in the models to find out if there were any possible learning effects. Although it has a positive effect, this is insignificant. Whether or not participants answered the probability question incorrectly had a significant impact on the probability of choosing the correct outcome. The effect is however small (less than 5%) The probability question was asked at the end of the end of the experiment and there was no incentive to answer it correctly.

Time Analysis

The total average response and review time for the 20 'lotteries' ranged from 25.5 to 63.3 seconds (sec). The average response time to answer each question was 29.9sec and participants took on average 7.5sec to review the results of each lottery. The distribution of the response time is shown in Figure 1.4 Shapiro-Wilk test for normal data indicates that the data is normally distributed: z= 16.6 (16.7 for total time), p<0.001.

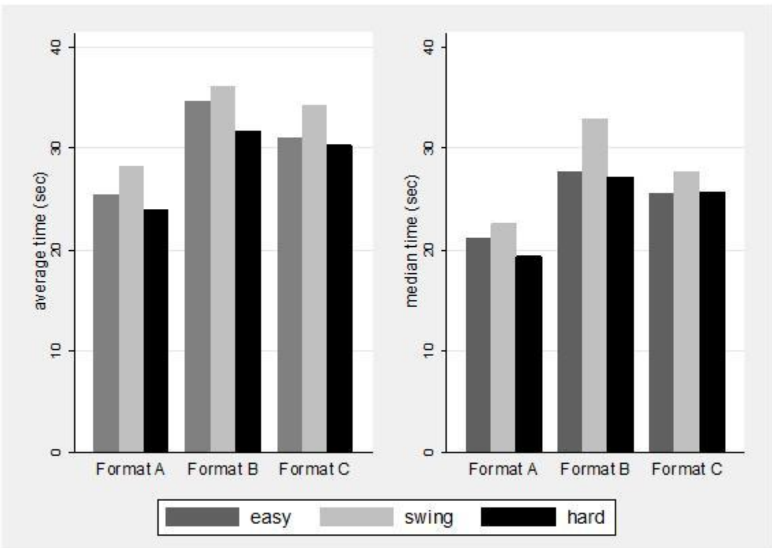
Figure 1.4: Distribution of response time



Result 5: Participants took on average less response time on the graph with uncertainty information compared to the table with uncertainty information.

The mean (s.d) response times for Format A, B and C were 25.8(17.7), 34.2(21.0) and 31.8(20.2) sec respectively. A one way ANOVA showed a statistically significant difference at the $p < 0.05$ level in response time for the 3 formats: F (2, 230) = 66.5, p<0.001. Post-hoc comparisons using the Tukey HSD test indicated that the mean response time for Format A was significantly lower than for Formats B and C. The average time difference between participants presented with uncertainty information was also statistically significant indicating participants spent more time on the table with uncertainty information compared with the graph. The latter is useful because it potentially means that the more visual graph with uncertainty information is cognitively easier to decipher information compared to the table. It therefore might be less costly as less time is spent on interpretation and understanding. Analyses using the average and median response times show significant differences in response time for the question type (i.e., easy, swing, and hard): F= 13.2, p<0.001; but no significant interaction between format and question type (Figure 1.7). The figure also shows that participants took more time on the table with uncertainty information despite the question type.

Figure 1.7: Average and median response times by format and question type



Post hoc analysis showed that participants took on average more time on the swing compared to hard or easy questions. ANOVA results at $p < 0.05$ show no significant time differences between the orders but the interaction between format and order is significant : F=15.1, p<0.001. Further analysis using regression (Table 1.7) also indicates that participants took more time on the table with uncertainty information compared to the graph although this is not statistically significant- the coefficient on the variable *Format B* is positive indicating this effect.

Result 5: Speed improved as the experiment progressed. In general, accuracy improved initially but had a drop towards the end of the experiment with differences between the orders.

There was a general decrease in the time participants took to respond to the questions as the experiment progressed (Figure 1.5). The same trend was found when analysed for the different formats and question orders (Figure 1.6) indicating a possible learning effect. Group A participants were faster than the other two groups whilst there seem to be little difference between Groups B and C. The decrease in time might, however, also indicate other effects such as the desire to finish the experiment. When analyzing all formats together, results indicate a gradual increase in ‘accuracy’ (which is measured by the proportion choosing the correct outcome) but it declines in the later rounds of the experiment. This is also the case for Format A and C participants; however for format B, accuracy gradually monotonically increases. Evaluation by format and order reveals a drop in accuracy rate much earlier for participants presented with order 2 (Appendix 1.5); whilst in some instances the accuracy rate first decreases and then increases about halfway through the experiment (for example Formats A and C using order 4, Formats A and B using order 3 and format B shown order 2).

Figure 1.5: Average response time participants took for each round

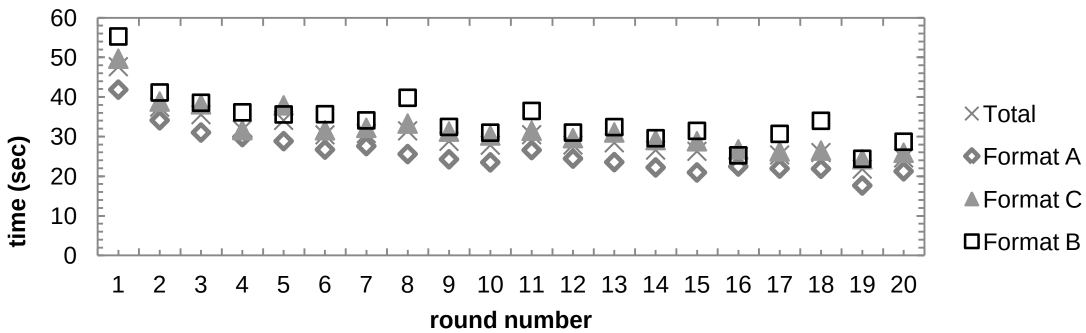
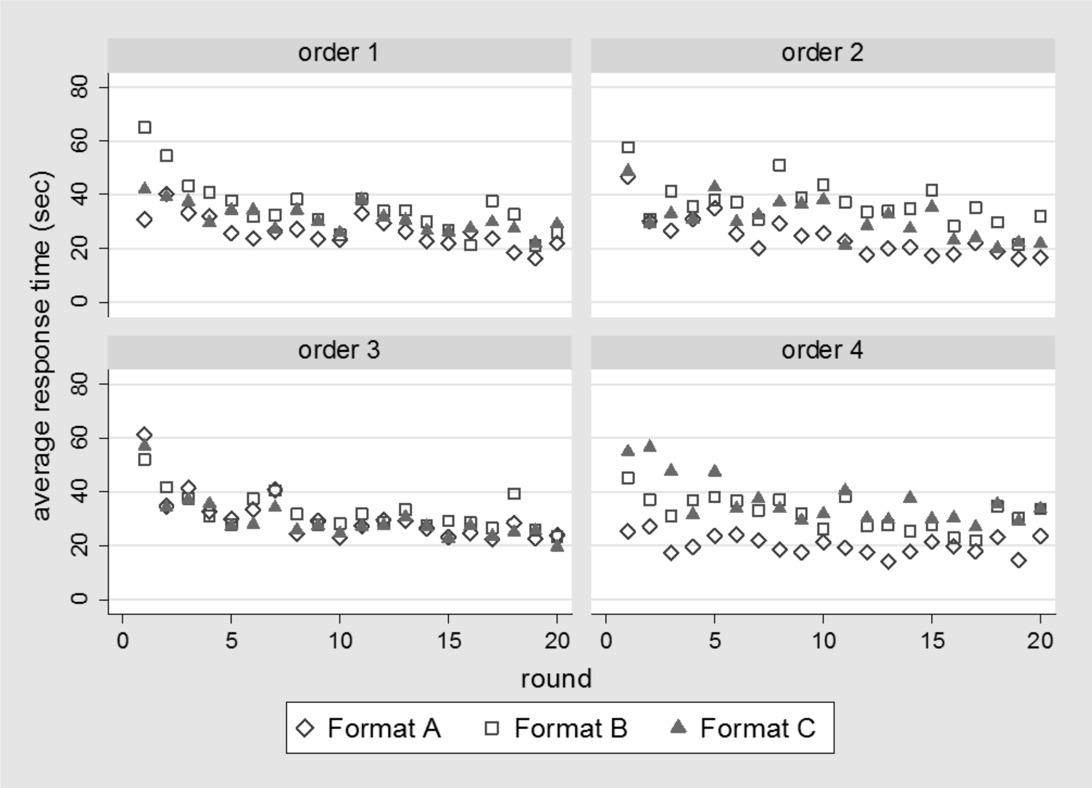


Figure 1.6: Average response times differentiated by question order



Determinants of response time for those provided with uncertainty information

Statistical analysis was done using multiple linear regressions (MLR) to assess the determinants of the time participants who were provided with uncertainty information took to respond to questions and, to test if the difference between Groups B and C is significant. MLR models the relationship between a dependent variable which in this case is response time and a set of independent variables. The time regression model measures the differences between Format B and Format C with the null hypothesis that participants who were shown the table with uncertainty information (Format B) would take more response time compared to participants who were shown the graph with uncertainty information (Format C), hence only data from participants who were shown the two formats was used. The regression model can be written as:

$$responsetime = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + ... + \beta_k\chi_k + \mu_i$$

where, β_0 is the intercept, β_i to β_k are the coefficients on the *k* independent variables, χ_i are the independent variables that affect *responsetime* (for example whether or not English is the first language) and μ_i is the error term which contains other explanatory variables which are not included in the model. The data used in the MLR was only from participants who were shown uncertainty information (Formats B and C) with the latter as the base group. Format B therefore equals one if participant was presented with a table with uncertainty information and zero if participant was presented with a graph with uncertainty information. Results of the MLR are shown in Table 1.7.

Further statistical analysis, supports a possible learning effect. The variable 'round number' shows a negative relationship with response time indicating that as the experiment progressed, participants were taking about 2sec less from round to round at the 1% level of significance, all other things constant. This might indicate a learning effect. The effect is negative until the 18th round with a decrease in time of 0.01s.[14]

Table 1.7: Results of linear regression analysis with response time as the dependent variable

Determinants	**Coef (s.e)**
Round number	**-1.991**(0.333)*******
Format B	1.536(1.024)
Swing question	-2.702(1.064)**
Swing & Format B	0.370(1.777)
Hard question	-0.612(0.960)
English is first language	-5.019(0.955)***
Male	1.136(0.751)
Age	0.418(0.123)***
Business	1.433(0.861)*
Checks weather every 2-3 days or less	1.826(0.740)**
Checks internet for weather forecast	-3.656(1.492)**
Above	0.273(0.776)
Early correct	0.705(0.750)
Probability question mistake	3.098(0.914)***
Round number squared	**0.055**(0.014)*******
Order 1	-3.806(1.126)***
Order 2	-2.346(1.193)**
Order 3	-4.260(1.132)***
Constant	43.26(3.664)***
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1	

Other effects

Demographic: Participants who indicated that English was their first language took 5.1sec less holding all the other factors constant. This result is expected since

[14] (-1.991 *2(0.055) (round number)). 0.055 is the coefficient on round squared

the experiment was conducted in English; the native speakers could probably understand more easily and faster compared to-non natives. Older participants took more response time at the 1% level of significance, holding all other things constant. Business school participants took more time compared to the Humanities but this is significant at a low level.

Experimental: Participants who answered the probability question incorrectly took 3.1sec more to respond holding all other things constant. Those presented with orders 1, 2 and 3 took significantly less time compared to those shown order 4.

Weather related variables: The weather variables, ‘Checks internet for weather forecast’ and ‘Checks weather at least every 2-3 days’ were significant determinants. The former shows a decrease in the time participants took to respond of 3.7sec whilst participants who indicated the latter took 1.8 sec more to respond, all other things being equal. Participants who check the weather on the internet are probably already familiar with other formats used to present weather forecast information hence their reaction times might be faster.

1.6. Conclusion

Experimental economics methodology was used to assess the impact of providing probabilistic weather information on forecast understanding and interpretation using different presentation forecasts to undergraduate students at the University of Exeter. Comparison was made between the performance of participants presented with uncertainty information presented in a table and bar graph format than if they were presented with a deterministic forecast based on the temperature up to five days ahead.

As in the previous study by (Roulston and Kaplan 2009), participants who were provided with uncertainty information correctly understood the forecast, interpreted it and used the forecast information to choose the most likely (“correct”) outcome compared to those without any uncertainty information. Initial descriptive analysis shows better performance for participants who were shown uncertainty information (Format B/C) despite the gender, academic department, or order in which questions were asked. Results indicate that participants who were provided with uncertainty information were able to use this information to correctly choose the most likely outcome, especially for the swing questions (for these questions, a hypothetical participant with just the point forecast, assuming mode=median, would result in that participant choosing a different option compared to those provided with uncertainty information.) There is not much difference for some of the non-swing questions between the three formats, with those with uncertainty information doing worse in some of the questions. Overall, for all questions, participants provided with uncertainty information performed better on average.

Providing uncertainty information may not always have been useful for some of the questions. In some instances (for the easy questions), participants presented with graph/table with uncertainty information might have made their decisions by choosing the outcome with the larger range below/above the specified temperature although this might not have been the most probable. Hence, it is possible that some did not understand or could not use the uncertainty information correctly. We however cannot definitively say that that is how some participants' interpreted the large ranges-the reason this might have occurred can be a subject for future research.

There was a general decrease in time spent per question as the experiment progressed for all the 3 groups. Statistical analysis shows a significant decrease in the time participants took to respond to questions as the experiment progressed coupled with a gradual increase in accuracy from round to round (measured as proportion choosing correct outcome as experiment progressed) up to the latter stages of the game when it declines. This possibly indicates a learning effect. This is useful as it shows that interpretation of a particular presentation of forecasts becomes easier with familiarity. Participants who were shown the graph with uncertainty information took on average less response time compared to those who were shown a table with uncertainty information. The graph was perhaps 'more visual' and cognitively easier for participants to interpret, understand and use information in less time compared to the table. Presenting information in a format that is both visually appealing and takes less time to process the information is useful as it reduces 'costs' for users. It therefore becomes important for providers of risk information such as the Met Office to invest in developing products that cater for this.

Assessing how weather information is disseminated to users is useful. Including information on uncertainty better represents the capability of the forecasts and provides the potential for better decision making, but information has to be communicated effectively in a format that users can interpret, use efficiently and avoid poor decisions. Results from our analysis can be used by the Met Office to help them decide which format to use to best disseminate weather information to the public and other partners, and to determine the value of presenting probabilistic information. Our general recommendations to the Met Office are: The Met Office should provide uncertainty information in temperature forecasts as it improves interpretation and understanding; there is need to assess and test different presentation formats that can be used to present weather forecasts to different users. More visual methods of disseminating weather forecasts for example graphs may get the message across to users faster as the method is perhaps more cognitively easier to decipher information; however, there is also need for the Met Office to take into consideration the possibility that the extra information may be incorrectly interpreted. Hence perhaps in some instances both the deterministic forecast and the uncertainty information can be provided depending on the user and type of weather forecast being provided. The Met Office should engage users throughout the product development process in order to ensure information is communicated effectively and to minimise misinterpretations.

Our results also add to the knowledge on weather forecast interpretation and decision making when provided with uncertainty information presented in a bar graph or table format. Research using the general public is also essential (the Met Office conducted a study using a weather game with the UK general public on their website- analysis is still underway).[15] A follow up study using the formats used in our study can be used to do assess real decision making, for example simple decisions such as whether or not to carry an umbrella or go out to a picnic, farmers deciding when to plant, whether or not to go ahead with a sport match; to national decisions such as deciding whether to evacuate people or fly a plane. Results can potentially help various sectors that use weather information which include agriculture, aviation, sports, energy, as well as policy makers and the general public. Other potential applications of the study include pensions giving risk advice,

[15] http://www.metoffice.gov.uk/barometer/features/2012-04/playing-the-game-of-uncertainty

brokers giving investment advice, and government displaying economic forecasts.

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Appendix 1.1: Experiment Instructions

'You are about to participate in an experiment involving the interpretation of weather forecasts. If you follow the instructions carefully and make wise decisions, you may earn a significant amount of money. Your earnings will depend on your decisions. Participants in this experiment do not interact with one another, so your earnings do NOT depend on the decisions of the other participants. All of your decisions will remain anonymous and will be collected through a computer network. Your decisions are to be made at the computer at which you are seated. Your total earnings from the experiment will be paid to you, in cash, at the end of the experiment.

Please turn off your mobile phone and do NOT attempt to communicate with the other participants. If you have any questions, please RAISE YOUR HAND and someone will come and help you. It is important that you understand the instructions. Misunderstandings may result in lower earnings.

The experiment consists of 20 repeated rounds. In each round you will be shown a graphic of the predicted maximum temperature over the course of the next few days, similar to the one below. You will also see two statement about the future weather, called Statement A and Statement B, for example:

Statement A – The maximum temperature on Saturday is above 12 °C
Statement B – The maximum temperature on Tuesday is above 15 °C

Statements A and B may or may not be true. In other words, neither statement may be true, both statements may be true or only one of the two may be true. The statements relate to the ACTUAL temperature. Your task is to study the graph, which shows the FORECAST temperature, and work out which statement is MORE LIKELY to be true.

You will begin each round by looking at the graphic and the statements and then choosing ONE of the two statements, either Statement A or Statement B. After you have chosen, you will be told the actual maximum temperatures on the days in question and therefore whether or not each statement is true. If you chosen statement is true, you will receive a payoff of 1 Feele token, otherwise you will not receive a payoff. Feele tokens will be converted into cash at the end of the experiment, at a rate of 50 pence per token. You will also receive a show-up fee of £3.00 for participating in this experiment.

There are NO trial rounds, so when you start 'Round 1', you will be playing for real money. Before you do so, however, you will be asked to answer some multiple choice test questions. The answers you give to these questions do NOT affect your payment; the idea is for you to get some practice reading graphs.

If you have any questions, either now or later on, please raise your hand and someone will come and help you.'

Appendix 1.2: Supplementary questions

1. What is your gender?
   (F) female; (M) male
2. Is English your first language
   (Y) yes; (N) no
3. Which of the following sources of information do you consult when you want to find out the weather forecast?
   (a) Internet; (b) TV; (c) Radio; (d) Newspaper; (e) Ask someone else
4. How frequently do you look at the weather forecast?
   (a) Never or hardly ever; (b) Weekly; (c) Every 2 or 3 days; (d) Daily; (e) More than once a day
5. If a fair die is rolled twice, what is the probability that a six will appear on both occasions?
   (a) 0; (b) 1/6; (c) 1/12; (d) 1/36; (e) None of the above
6. What strategies did you use to make your decisions?

Appendix 1.3: Analysis of variance

Average number of correct answers

			Format A		Format B		Format C	
			n	Mean(s.d)	n	Mean(s.d)	n	Mean(s.d)
All questions	All		87	13.2 (1.7)	38	15.6 (2.6)	105	15.0 (2.5)
	Department	Business	35	13.0 (1.2)	19	15.9 (3.0)	64	15.1 (2.7)
		Humanities	21	13.3 (2.1)	19	15.2 (2.2)	41	14.9 (2.1)
		Sciences	31	13.5 (1.9)				
	Sex	Female	45	13.0 (1.9)	19	14.8 (2.9)	57	14.5 (2.6)
		Male	42	13.5 (1.3)	19	16.3 (2.1)	48	15.6 (2.1)
	English first language	No	21	12.5 (1.7)	15	16.1 (1.9)	33	14.6 (3.2)
		Yes	66	13.5 (1.6)	23	15.2 (3.0)	72	15.2 (2.1)
Swing questions	All		87	1.1 (1.1)	38	3.6 (1.4)	105	3.6 (1.1)
	Department	Business	35	1.1 (0.9)	19	4.1 (1.3)	64	3.7 (1.2)
		Humanities	21	1.0 (1.0)	19	3.2 (1.4)	41	3.4 (1.0)
		Sciences	31	1.0 (1.3)				
	Sex	Female	45	1.2 (1.2)	19	3.3 (1.6)	57	3.4 (1.2)
		Male	42	1.0 (0.9)	19	4.0 (1.2)	48	3.8 (1.0)
	English first language	No	21	1.3 (1.0)	15	3.8 (1.2)	33	3.6 (1.2)
		Yes	66	1.0 (1.1)	23	3.5 (1.5)	72	3.6 (1.0)
Non-swing questions	All		87	12.2 (1.6)	38	11.9 (1.9)	105	11.4 (2.1)
	Department	Business	35	11.8 (1.6)	19	11.8 (2.3)	64	11.4 (2.3)
		Humanities	21	12.2 (1.9)	19	12.0 (1.5)	41	11.4 (1.8)
		Sciences	31	12.5 (1.5)				
	Sex	Female	45	11.8 (1.7)	19	11.5 (2.1)	57	11.1 (2.4)
		Male	42	12.5 (1.5)	19	12.3 (1.6)	48	11.9 (1.7)
	English first language	No	21	11.2 (1.8)	15	12.3 (1.6)	33	11.0 (2.7)
		Yes	66	12.5 (1.5)	23	11.7 (2.0)	72	11.7 (1.8)

ANOVA with number of correct answers as dependent variable

	Model 1				Model 2				Model 3		
	d.f	F	p		d.f	F	p		d.f	F	p
format	2	16.1	**0.000**	format	2	21.9	**0.000**	format	2	20.7	**0.000**
school	2	0.4	0.648	male	1	11.4	**0.001**	english	1	0.4	0.514
format * school	2	0.6	0.564	format * male	2	0.8	0.450	format * english	2	2.4	0.098

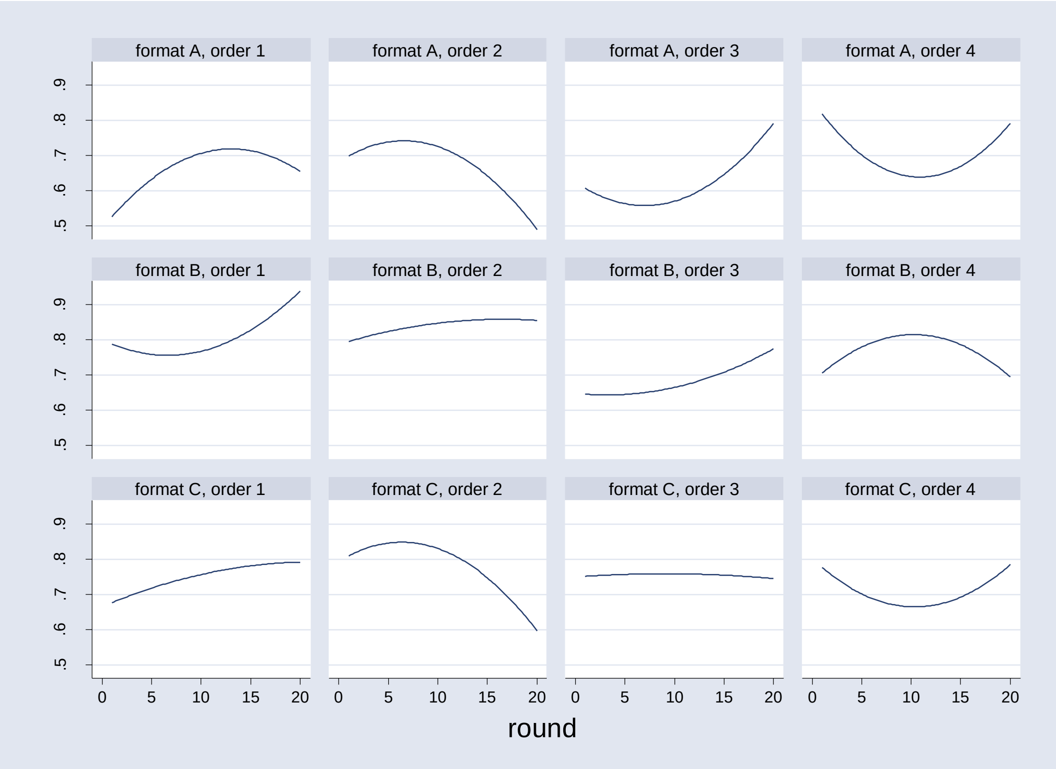
	Model 4				Model 5				Model 6		
format	2	17.0	0.000	format	2	21.7	0.000	format	2	12.3	0.000
male	1	7.4	0.007	male	1	11.9	0.001	school	2	0.3	0.773
school	2	0.5	0.622	english	1	0.0	0.919	english	1	0.2	0.663
format* male	2	0.3	0.737	format* male	2	0.8	0.475	format* school	2	0.6	0.569
format* school	2	0.4	0.653	format* english	2	2.6	0.074	format* english	2	1.4	0.245
male* school	2	1.2	0.304	male* english	1	0.0	0.947	school* english	2	0.1	0.936
format*male *english	2	0.6	0.553	format*male *english	2	1.9	0.160	format*school *english	2	2.6	0.081

Appendix 1.4: Description of variables

All variables used were binary except for time, 'round' and interaction terms with round

Predictor	Description
Above	=1 if question asks for temperature *above* X deg. C, 0 if it asks for *below*
Area	1= questions where the greatest area between the high/low range and the asked temperature does not get the correct answer for Group C participants for questions 1,12 and 13
Business	=1 for participants studying business/economics related subjects and 0 if science/humanities
Checks internet for weather forecast	1=checks internet for weather forecast
Checks weather at least every 2-3 days	1=if participant checks weather at least every2-3 days, 0= checks weather weekly or never
Die question mistake	1=participant answered the question about rolling a fair die twice incorrectly
Early day correct	=1 if statement A was the most probable outcome (e.g. Monday as opposed to Wednesday)
English is first language	1= English is first language, 0=otherwise)
Format A	1= participant was presented with a table with point forecast
Format B	1= participant was presented with a table with uncertainty information
Format C	1= participant was presented with a bar graph with uncertainty information
Hard question	1= question is hard, 0=swing/easy
Humanities	1= participant is from humanities department
Length	1= questions where the greatest length between the high/low range & the asked temperature does not get the correct answer for Group B participants for questions 1, 12 and 13.
Male	1=male, 0= female
Order 1	order is: 1, 2,..., 20
Order 2	order is: 20, 19,..., 1
Order 3	order is: 11, 12,..., 20, 1, 2,..., 10
Round number	Round number
Round number squared	Round number squared
Sample question mistake	1= participant answered two of the test questions incorrectly
Swing question	1=question is a swing question, 0= hard/easy
Test question dummy	1= test questions worded as 'most likely' , 0 = worded as 'expected'
Response time	average response time taken by a participant to respond for each of the 20 'lotteries

Appendix 1.5: Change in accuracy as experiment progressed



Graphs show results of fitting of a quadratic function. Accuracy was measured as the proportion of participants choosing the correct outcome for each round. Fitted equation was: proportion choosing safe outcome = round + roundsquared.

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CHAPTER 2: Gender differences in risk and ambiguity attitudes among Zimbabwean farmers

2.1. Introduction

Smallholder farmers constantly face risk and ambiguity at all levels of the agricultural production cycle: production, processing, storage and marketing. These include natural environmental calamities such as droughts, floods; pests and diseases; financial risks; human resource risks; institutional risks (for example change in government policies); to price and market related risks. Managing these risks is important as it has serious implications on food security and farmers' livelihoods.

There are a number of coping mechanisms that farmers can implement to manage risks, which include adopting new technologies such as drought tolerant varieties, hybrid varieties, new fertilizers, or strategic decisions such as crop diversification, crop sharing, sale of assets among others. Important questions therefore arise such as: How do smallholders behave or make decisions when faced with risk and uncertainty? Why do they or do they not adopt some strategies? At what risk level do smallholder farmers employ certain strategies? Does their socioeconomic background and gender influence their behaviour? This chapter assesses the adoption of a drought tolerant crop variety under different probabilities of a drought occurring. The purpose of the study was to determine at what risk levels farmers would be willing to adopt a drought tolerant variety and factors affecting this decision- and to assess if there were differences under risk and ambiguity from a gender perspective. The study compares the risk and ambiguity attitudes of male and female smallholder farmers. Eliciting risk aversion and whether or not there are gender differences in farmers' ambiguity aversion can potentially help agricultural development planners and policy makers to make more informed decisions.

Most studies done with small scale farmers in developing countries show that they are risk averse (Brüntrup 2000, Yesuf and Bluffstone 2009, Belaid and Miller 1987, Teklewold and Köhlin 2011, Dillon and Scandizzo 1978), whilst studies on ambiguity aversion in developing countries are limited and produce inconsistent results. In some studies, researchers have found no evidence of ambiguity aversion (Henrich and McElreath 2002) whilst others have concluded that smallholder farmers are ambiguity averse (Akay et al. 2010).

Women play a key role in smallholder agriculture. A recent Food and Agriculture Organisation (FAO) time use study shows that women's contribution to agricultural activities in Sub- Saharan Africa range from about 30 percent in Gambia to 60-80 percent in different parts of Cameroon (FAO 2011). FAO, however also notes that a contribution to agricultural output by gender is difficult to infer as both men and women are involved in production. Evidence suggests that women are more concerned about family subsistence relative to men and are more likely to spend on goods and services that improve the family's welfare (Thomas 1993, Garcia 1991, Hoddinott and Haddad 1995, Lawson, Gilman and Goldman 2009). In Côte d'Ivoire, (Duflo and Udry 2004) find that when income from 'women crops' is higher, households allocate more of their budget to food and private goods for women; but when the production from 'men's crops' is higher, households spend a bigger share on alcohol, tobacco and goods consumed by men. An increase in the management of resources controlled by women and decision making has positive effects on education, child nutrition, health and the welfare of women themselves (Quisumbing and McClafferty 2006, pg 12, Quisumbing 2003). Given that individuals in households may have different preferences and may not necessarily act as a 'unit'[16] when making decisions and evidence that women's decision making improves aspects of household welfare, it becomes important to elicit risk and ambiguity preferences from a gender perspective.

Understanding risk and ambiguity preferences from a gender perspective is important as it enables us to assess whether or not women and men respond to risk/ ambiguity differently; which has potential implications in their economic and social decision making process. There is a general consensus that women are more risk averse compared to men (e.g. in investment (Gong and Yang 2012, Charness and Gneezy 2012, Schubert et al. 1999, Powell and Ansic 1997); in market trade (Fellner and Maciejovsky 2007), but very few studies have been undertaken that specifically compare men and women's risk and ambiguity aversion attitudes in smallholder agriculture. In a study in Ethiopia, female

[16] Empirical evidence indicates that households do not follow the 'unitary' model (individuals in household have the same preferences and they pool their resources) and this has given rise to alternative collecting models that allow for differences in individual preferences (see Haddad et al., 1997 for reviewed studies). A household member's bargaining power determines intrahousehold allocation outcomes.

household heads were more risk averse compared to their male counterparts (Yesuf and Bluffstone 2007). Schubert et al. (1999) found evidence of women being more ambiguity averse in investment but not in insurance. Framing a gamble as either a 'loss' or 'gain' can influence an individuals' risk attitudes. Schubert et al (1999) conclude that men are more risk-prone toward gains whilst women are more risk-prone toward losses; however other studies have shown no significant gender differences in risk or ambiguity aversion in both loss/ gain gambles (Moore and Eckel 2003). Some studies also show no evidence of systematic gender differences in risk attitudes for experiments with a contextual environment (Schubert et al. 1999, Kruse and Thompson 2003)[17].

This study contributes to the risk and ambiguity preferences literature in that it measures both ambiguity and risk preferences of smallholder farmers from a gender perspective. Often, studies done in developing countries with farmers focus on one of the two, either ambiguity or risk aversion but not both and we found no studies that exclusively focused on gender differences. We survey the existing literature in Section 2.2.2. Ambiguity aversion and risk aversion are important elements in technology adoption hence the need to assess both factors in order to better understand behavioural determinants of farmers' choice in contexts where the risk is known and also in areas of technology uptake/adoption and investments which are characterised by unknown risks (ambiguity) for example yield distributions. Our method of elicitation for ambiguity attitudes, which involves the use of imprecise probabilities (range of probabilities/ probability intervals), is also rare in empirical studies on decision making in developing countries. Subjects in one group are presented with a risky lottery whilst another group is presented with an ambiguous lottery.

We asked farmers to determine what proportion of their total land they would allocate to the drought tolerant variety if they choose to adopt. Subjects choose whether or not to adopt a drought tolerant variety, given different ambiguity and risk levels of a drought occurring. In most studies, farmers are already adopters of new technologies and they are asked ex post to indicate how much land they actually allocated. However, in our case, the new variety is hypothetical and farmers

[17] For a summary of findings of gender differences in risk and ambiguity behaviour under abstract gamble and contextual environment experiments see Eckel, C. C. & P. J. Grossman (2008b) Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results,* 1**,** 1061-1073.

indicate the proportion ex ante.

2.2. Literature review

Risk aversion and ambiguity aversion: Theory

This section will give an overview of theoretical background and empirical evidence on risk and ambiguity aversion. A lot of theoretical and empirical work has been done on decision making under risk and uncertainty. Knight (1921) was probably one of the pioneers to distinguish risk and uncertainty, with the former being measurable uncertainty and the latter as 'unmeasurable uncertainty'. In explaining risk and uncertainty and subjective utility theory in agriculture, Ellis (1993) notes that the economic analysis of risk is not based on *objective* but rather *subjective* risk i.e. in most decisions what is relevant is not the assumption of knowledge about the likelihood of certain events but rather the decision maker's (DM) *personal degree of belief* about the occurrence of events which will determine the action a farmer will take. Though past records of the weather can help calculate the objective probability of a drought occurring, the farmer's personal view will determine his/her course of action. Risk is therefore the 'subjective probabilities attached by farm DMs to the likelihood of occurrence of different events' whilst uncertainty refers to the economic environment faced by farmers which will contain various uncertain events 'to which farmers attach various degrees of risk, according to their subjective beliefs of the occurrence of such events.' (Ellis, 1993).

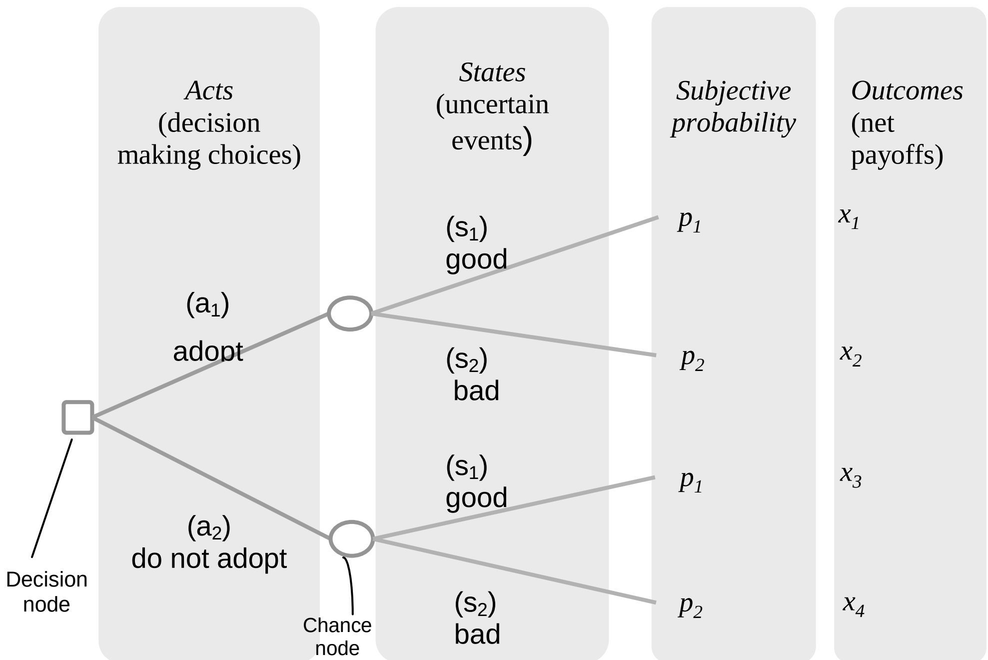
Risk aversion is when an individual prefers a certain option compared to an uncertain one even though the later might have higher expected payoffs, thus minimising their potential losses. The concept of risk aversion has its foundations in the Expected Utility Theorem (EUT) which is the classical model on decision making under risk. The EUT was initiated by Bernoulli (1738) and then formally developed by von Neumann and Morgenstern (vNM) (1944) who provided axioms[18] that were necessary and sufficient for EU over lotteries. Following vNM Theory, Savage (1954) and later (Anscombe and Aumann 1963) developed the Subjective Expected Utility model (SEU). Unlike in EUT, where probabilities associated with a lottery are known, probabilities are not necessarily objectively

[18] The main axioms are: completeness (For every A and B, either $A \succsim B$ or $B \succsim A$), transitivity (If $A \succsim B$ and $B \succsim C$ then $A \succsim C$), continuity (If $A \succsim B \succsim C$ then there is a lottery which gives A with probability p and C with probability (1-p) for which the individual is indifferent with B, and independence (If $A \succsim B$ then the individual prefers the lottery which gives A with probability p and C with probability (1-p) to the gamble which gives B with probability p and C with probability (1-p), for any p, C.)

known under SEU. Individuals form a personal probability distribution and choose among the resulting lotteries.

Decision theory can be facilitated by the use of a decision tree (Figure 2.1). When deciding, individuals may have to make a choice between different *alternatives* or *courses of action* which are assumed to be mutually exclusive and exhaustive. In our case, the courses of action are deciding whether or not to adopt a drought tolerant variety which branches off from the *decision node*. These alternatives however depend on *states of nature* $(S_1, \ldots, S_n)$which are beyond the control of the decision maker such as whether or not a drought will occur or in another context it might be the demand for a certain product.

Figure 2.1: Decision tree analysis of a risky decision problem

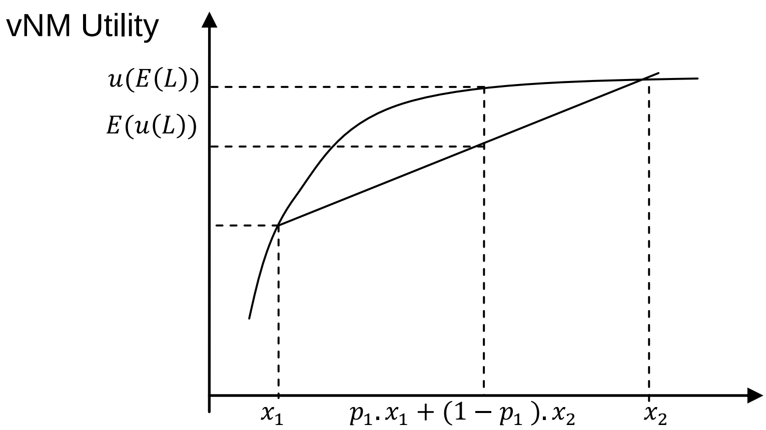


Source: Adopted from Ellis (1993), pg 93

The states may occur with either alternative thus they are duplicated from the *chance node* of each alternative. The combined effect of the chosen course of action and state of nature will eventually determine *outcomes* $(x_1, \ldots, x_n)$ whose values are measured as utilities*.* Decision making under risk and uncertainty will involve attaching certain probabilities or range of probabilities to the states of nature such that each action has its own probability distribution $(p_1, \ldots, p_n)$ of outcomes. EUT postulates that, a decision maker will choose between alternatives by comparing the expected utility values and maximises the probability weighted sum of the utility of the outcomes ($\sum p_i \times u(x_i)$); thereby choosing an alternative whose associated probability distribution of outcomes has the maximum expected utility. Under EUT, the shape of one's utility function conventionally defines his/her risk preferences. Concavity represents risk aversion, whilst a convex and linear utility function denotes risk loving and risk neutrality behaviour respectively.

Define a fair lottery (L) (i.e. expected value =0) with outcomes $x_1$and x_2 and probabilities p_1 and $1 - p_1$ respectively such that, $E(u(L)) = p_1.u(x_1) + (1 - p_1).u(x_2)$. An individual is considered *risk averse* if and only if (iff) they reject all fair gambles: $E(u(L)) < u(p_1.x_1 + (1 - p_1).x_2) \equiv u(0)$. Remember a function (f) is strictly concave iff $f(\lambda x + (1-\lambda)y) > \lambda f(x) + (1-\lambda)f(y)$ for all $\lambda \epsilon (0,1)$. Therefore a risk averse individual will have a strictly concave utility function and will prefer a certain payoff to a gamble giving the same expected return $u[E(L)] > E[u(L)]$ as illustrated in Figure 2.2. Risk neutrality is indifference to a fair gamble whilst risk loving behaviour will entail opting for the gamble.

Figure 2.2: Illustration of risk aversion



Over the years, the EUT has come under criticism as experimental work has shown that individuals systematically violate the assumptions underlying EUT. This has led to alternative models being proposed. Alternative theorems include Rank Dependent Utility Theorem (Quiggin 1982) and Prospect Theory (Kahneman and Tversky 1979, Tversky and Kahneman 1992). In their analysis of the EUT and Prospect Theory (PT), Harrison and Rutström (2009) concluded that there is no one true model that is exclusively the correct model but these models are correct for different parts of the sample or decisions. PT has proven in some instances to have more predictive power compared to the EUT (Abellan-Perpiñan, Bleichrodt and Pinto-Prades 2009).

Ambiguity aversion

Ellsberg (1961) demonstrated *ambiguity aversion* and showed that individuals prefer to bet on a lottery with known probability (risk) as compared to one with unknown probability (ambiguity) even though the lotteries might have subjectively equivalent probability, thus violating the EUT. In his paper, Ellsberg defines ambiguity as, "...a quality depending on the amount, type, reliability and "unanimity" of information, and giving rise to one's degree of "confidence" in an estimate of relative likelihoods", which can be characterised to exist between the extremes of 'risk' and 'ignorance'(Yates and Zukowski 1976).

A generalised definition of ambiguity given by (Camerer and Weber 1992) is "uncertainty about probability, created by missing information that is relevant and could be known." In ambiguous situations, there is 'uncertainty about the uncertainty' as we cannot always assign exact probabilities; for example when making decisions a DM who is told the probability of an event occurring is 20% will probably not make the same decision as one who is told the probability is 10-30%. SEU predicts that ambiguity, like the latter case, does not affect decision making and consumers presented with the information above should make the same decision. However, as evidenced by various empirical results, that is not the case, leading to the concept of *ambiguity aversion*. In one of his experiments, Ellsberg proposes that in an urn containing 90 balls, 30 balls are red (R) and the remaining 60 are either black (B) or yellow (Y), but in unknown proportions. If one ball is drawn at random from the urn consider the following lotteries:

L1: Receive $100 if R, otherwise nothing

L2: Receive $100 if B, otherwise nothing

L3: Receive $100 if R or Y, otherwise nothing

L4: Receive $100 if B or Y, otherwise nothing

Ellsberg predicts that most people prefer L1 to L2 and when choosing between L3 and L4, they preferL4 to L3 thus contradicting the "sure thing principle" from SEU. A preference of L1 to L2 means we should also prefer L3 to L4 as the (L3; L4) pair simply adds $100 for drawing a yellow ball to the (L1; L2) pair. Sure thing principle: $R \succ B \Longrightarrow R+Y \succ B+Y$.

Camerer and Weber (1992) review various theories proposed to describe ambiguity aversion and group them into four main categories; utility-based models (Smith 1969), models based on unique second order probabilities (SOPs) (Kahn and Sarin 1988), models based on sets of probabilities such as Gilboa and Schmeidler's (1989) maxmin expected utility, models without SOPs (Einhorn and Hogarth 1985) and Choquet expected utility theory (Schmeidler, 1989). Other recent models include: KMM smooth ambiguity model (Klibanoff, Marinacci and Mukerji 2005), multistage recursive model (Nau 2006) and the non-expected utility model of source functions (Abdellaoui et al. 2011) to mention but a few.

2.2.1. Eliciting risk and ambiguity preferences using experimental economics

This section provides a summary of experimental economics and experimental methods used to elicit risk and ambiguity preferences.

Ambiguity and risk attitudes can be elicited from agricultural producers using actual production data, surveys or economic experiments. In this study, we will use the latter to measure ambiguity and risk preferences. Experiments, which can either be conducted in the field or in a laboratory, are useful in economics as they help us to better understand some of the fundamental questions in economic theory and also to determine the validity of various economic theories, for example regarding human behaviour in auctions, public goods provision, bargaining, attitudes towards risk, and so forth. Participants are normally incentivised with real monetary payoffs.

Most experimental studies use undergraduate students as participants because they are readily available especially in a university setting; and in terms of incentives, it is cheaper and fairly easy to recruit them. However, one of the debatable issues on the use of 'non-experienced' students in the laboratory is the potential lack of external validity of experimental research i.e. whether or not people in the real world/ professionals in a certain area behave that way. The use of experimental economics in the field takes care of the issue of lack of external validity and subjects usually have the necessary experience that will be more directly related to the research questions (Carpenter, Harrison and List 2005).

Field experiments are normally done with a non-student population and they “provide a bridge between laboratory and naturally-occurring data in that they represent a mixture of control and realism usually not achieved in the lab or with uncontrolled data permitting the analyst to address questions that heretofore were quite difficult to answer” (Levitt and List 2009). This study will investigate the risk and ambiguity attitudes of non-standard subjects (smallholder farmers).

Various approaches exist to elicit risk and ambiguity preferences in experimental economics. Harrison and Rutström (2008) give a comprehensive discussion of the shortcomings and strengths of 5 main methods. The main procedures are: Multiple Price List (MPL) (e.g., Holt and Laury 2002b, Charness and Viceisza 2012), Ordered Lottery Selection (e.g., Barr, 2003; Binswanger, 1980; Binswanger, 1981), Random Lottery Pair Design (see, Hey and Orme, 1994), Becker-Degroot-Marshak (Becker et al., 1964; Harrison, 1986) and the trade-off method (Wakker and Deneffe, 1996). Ambiguity aversion is typically elicited using Ellsberg (1961) urn experiments or variations (see., Pulford and Colman 2008, Camerer and Weber 1992, Keren and Gerritsen 1999, Liu and Colman 2009) or the Becker-Degroot-Marshak method where the difference in the willing to pay for the ambiguous and risky gambles measures ambiguity aversion.

Our research uses MPL to elicit the risk and ambiguity preferences of Zimbabwean smallholder farmers. In typical MPL, participants are asked to make a series of choices from a list of binary lotteries or choices between a lottery and a sure payment with varying probabilities and fixed payoffs. The experiment is therefore designed in such a way as to incentivise the participant to ‘switch’ from one option to the other. The switch point produces an interval estimate of the participant’s risk preference. MPL is normally preferred because it is simple to explain, implement and elicit true valuations especially in instances where individuals have low education levels and it yields less noise compared to other methods (Galarza, 2009). Disadvantages include: susceptibility to framing effects, the method only elicits interval responses rather than “point” valuations and potentially inconsistent preferences as subjects switch back and forth from as they move down the decision rows.

2.2.2. Summary of studies using field experiments to elicit risk and ambiguity attitudes in developing countries

This section gives an overview of existing literature on studies eliciting the risk and ambiguity attitudes of farmers in developing countries. The use of field experiments with farmers dates back to Binswanger (1980) who investigated the risk attitudes of Indian farmers. Ever since then a number of studies have been done in developing countries using experimental economics techniques to elicit risk and ambiguity attitudes.

Binswanger (1980) used two methods to measure the risk attitudes of farmers; an experimental ordered lottery selection with real payoffs and an interview method eliciting certainty equivalents. Most of the farmers were moderately risk averse and risk aversion tended to increase with higher payoffs. Farmers displayed behaviour consistent with both increasing relative risk aversion (IRRA) and decreasing absolute risk aversion (DARA). Using a modified version of the Binswanger (1980) experiments, Belaid and Miller (1987) undertook experiments with choices that included both loses and gains to smallholder farmers in different agro-ecological zones in Algeria. Sampled farmers exhibited risk averse behaviour and no intrinsic differences in farmers' risk attitudes between sites or agro-ecological zones were found. Henrich and McElreath (2002) also used a Binswanger (1980) type of experiment to compare the preferences of different groups of smallholder farmers, the Mapuche in Chile and the Sangu in Tanzania. Their results differ from the general consensus of risk aversion in subsistence farmers and instead they find risk seeking behavior among the Mapuche and Sangu. Their method of elicitation used CEs after providing participants with a series of options between a sure option and a fixed risky bet. 'Cultural group' was a significant determinant of risk preferences whilst none of the demographic or economic variables were significant determinants. As in (Binswanger 1980), wealth had a negative relationship with risk preferences but this was not statistically significant.

Charness and Viceisza (2012) and Ihli et al. (2013) compare different elicitation methods in rural Senegal and Uganda respectively. Charness and Viceisza compare an HL type experiment, a non -incentivized willingness-to-risk (WRT) scale and a simple binary method pioneered by (Gneezy and Potters 1997) where participants decided how many *risky seeds* they wished to purchase given different payoffs under equally likely good and bad weather. They find high levels of inconsistency in the HL type experiments and they report that no more than a quarter of the respondents made consistent and sensible (non-dominated) responses. These results are consistent with (Galarza 2009); however other studies with smallholder farmers have found relatively low inconsistency levels (de Brauw and Eozonou 2011, Ihli et al. 2013). The simple binary method produces results consistent with previous studies but Senegalese farmers were more risk averse whilst the WRT scale indicated women were more likely risk seeking. The authors conclude that, 'simpler is better and that incentives appear to matter when eliciting risk preferences in developing nations.' Ihli et al. (2013) compare a modified HL with the procedure used by (Brick et al. 2012). Brick et al (2012) use an MPL design but unlike HL, probabilities are fixed (100% for option A and 50/50 for option B) and payoffs vary. Ihli et al (2013) find differences between the two methods. Participants are more risk averse in the modified HL compared to the modified Brick method. Wealth and probability scores have a positive significant relationship with risk aversion in both methods. Education, farm size, district and winning in the first lottery-choice experiment are significant factors in the HL only.

Harrison et al. (2010) and de Brauw and Eozonou (2011) test which theory best models the risk preferences of farmers. Results from Harrison et al indicate that more than half of the participants from India, Ethiopia and Uganda followed the expected utility theory (EUT) and the rest behaved according to prospect theory (PT). Inferences about the degree of risk aversion were not affected by which of the two models was assumed. When they estimated a finite mixture model, both models explained the data: risk averse behaviour was inferred from EUT following subjects whilst risk seeking was inferred for PT followers. Using Mozambican farmers as subjects, de Brauw and Eozonou show that farmers' preferences follow the power risk aversion preferences instead of the constant relative risk aversion (CRRA) utility function. In a mixture model, most of the farmers (about 75%) develop risk preferences by rank dependent utility (RDU) and the rest follow EUT. The authors also show that incorrectly assuming CRRA, poorly predicts the risk preferences of the less risk averse farmers. Caution should therefore be taken regarding what assumptions to make when eliciting risk preferences. Women were less risk averse compared to men in the Harrison et al study which is a deviation from the general finding, and age has a significant positive effect on risk aversion.

Tanaka, Camerer and Nguyen (2010), conduct experiments with Vietnamese villagers to find out the predictors of risk and time preferences using cumulative prospect theory (CPT). Villagers from wealthier villages were less risk and loss averse. The study found correlation between household income and time preference but none with risk preference. Experiments similar to Tanaka et al were also conducted with Chinese farmers who had adopted genetically modified cotton. Their results emphasize that technology adoption decisions are affected by farmers' perceived risk and potential loss from adoption. Cotton farmers who were more risk averse or loss averse adopted later whilst those who overweighed small probabilities were earlier adopters.

A few studies were found that elicited both ambiguity and risk preferences. (Alpizar, Carlsson and Naranjo 2011, Akay et al. 2010, Engle-Warnick, Escobal and Laszlo 2007, Engle-Warnick, Escobal and Laszlo 2011). Results from these studies indicate the importance of assessing both the risk and ambiguity preferences of smallholder farmers. Akay et al (2010) use a variation of Henrich and McElreath (2002) experiments among Ethiopian peasants and find evidence of high risk averse and ambiguity averse behaviour. To measure ambiguity aversion, they use the 2 colour Ellberg urn choice task. More than half of the participants were highly risk averse or ambiguity averse(58% and 57% respectively). Poor health increased both ambiguity and risk aversion whilst risk aversion had a positive relationship with household size. Marriage reduced ambiguity aversion.

Alpizar et al (2011) conducted their experiments in Costa Rica, a few months after an unexpected tropical storm. Participants had to choose whether or not to adapt to climate change based on known (1%, 5%, and 10%) and unknown risk levels (between 1 and 10%). Most of the farmers were risk averse and farmers who did not adopt at low risk levels exhibited ambiguity averse behaviour. However, they find no evidence of ambiguity aversion in the aggregate data. They also investigate the impact of communication and monetary incentives on decision making: their results indicate a significant increase in the degree of adaptation with monetary incentives and with communication; farmers were coordinating more frequently to reduce their adaptation costs.

Engle-Warnick et al (2007,2011) show that both risk aversion and ambiguity aversion are important in farmers' decision making in Peru using a variation of

OLS. Risk preferences are measured by providing participants with four gambles with choices between a relatively safe and a relatively risky gamble. Ambiguity aversion is measured by the number of times a subject pays to avoid an ambiguous gamble after presenting participants with five decisions. In one gamble the probability distribution over outcomes is unknown whilst in the other gamble, there is a 50/50 chance of winning the same prize. If a subject chooses the latter they were required to pay a certain amount from their final earnings for the choice.In their 2007 paper on technology choice, they find that technology choices are predicted by ambiguity preferences rather than risk preferences. Individuals from larger families were more risk seeking, poorer farmers were more risk averse and farmers who owned part or all their land were more risk averse than tenant farmers. Farmers exhibiting ambiguity averse behaviour were less willing to diversify across varieties and the higher the degree of ambiguity aversion, the less the diversification but this is not the case with risk aversion. Engle-Warnick et al. (2011) provide evidence that shows that ambiguity averse farmers are less likely to plant more than one variety of their main crop whilst the same cannot be said about risk aversion.

Adoption and risk /ambiguity attitudes

When adopting new technologies, farmers' decisions might depend on whether or not they value more the losses or the gains they might incur if they adopt. If the new technology is relatively unknown to them and offers a possible loss, then they may choose not to adopt. Alternatively, the new technology may be preferred if the expected payoff is higher and its exposure to risk and ambiguity is lower (Barham et al. 2011). Disease/pest resistant or drought tolerant varieties are some examples of technologies that can reduce exposure to risk and ambiguity. Our experiment is a choice between a traditional variety and a new variety that is drought tolerant. According to (Rode et al. 1999), decisions with known probabilities have a low range of possible mean payoffs and variance, whilst for ambiguous choices the range of possible mean payoffs and variance is high. Therefore, individuals associate ambiguous probabilities with highly variable outcomes and avoid them.

Results on whether or not adoption of new technologies is influenced by either an individual's ambiguity attitudes, risk attitudes or both have been inconsistent, with some studies indicating that choices of technology adoption are more linked to ambiguity aversion as opposed to risk aversion (Engle-Warnick, Escobal and Laszlo 2006, Ross, Santos and Capon 2010). A study on climate change adaptation with smallholder farmers in Costa Rica found evidence of ambiguity aversion for the farmers who did not adapt at low risk levels (Alpizar et al. 2011). Using experimental economics techniques, this chapter will explore the impact of the level of risk/ ambiguity of a drought occurring on whether or not farmers will adopt a new crop variety. The risk and ambiguity aversion of smallholder farmers will be elicited and differences compared from a gender perspective.

2.3. Experimental design

The experiment followed the design by Holt and Laury (2002). Our experiment involved making a series of 10 choices from two options. Participants were asked to choose whether or not to adopt a new drought tolerant maize crop variety after being told the exact probability of a drought occurring (e.g. 40% probability of drought) or the range (e.g. 20-60% probability of drought). Adoption was the safe choice (Lottery A) whilst non-adoption was the riskier one (Lottery B). Participants were presented with *either* the exact probabilities (i.e. all the 10 decisions showed the exact probability) *or* the range of probabilities and not a mixture; hence there were two groups of participants. Participants were also informed that the new maize crop variety could do well in both rainy and drought conditions. The payoffs presented to participants are shown in Table 2.1. The experiment instructions are in Appendix 2.1.

The payoffs were fixed across the decision rows whilst the probabilities varied. The ambiguous lotteries were derived from the risk lotteries such that for a risk lottery which offered payoff of x with probability p, the equivalent ambiguous lottery would offer the same payoff x with probability which is between p_{min} and p_{max} (where $p_{min} = p - r$ and $p_{max} = p + r$, r = probability width interval) and $p = (p\_min + p\_max)/2$, for example at 30% probability of drought, the risk option (lottery A) for decision 3 would be (4,30% ; 6,70%) whilst the corresponding ambiguous lottery will be (4, [25%,35%] ; 6[otherwise]). Simply, the probability of the risky treatment was the centre of the range in the ambiguous treatment for each decision choice. The probability interval for the ambiguous lotteries was fixed at 10%.

Table 2.2 shows the expected values of the two lotteries and CRRA interval at switch point for the experiment. If risk neutral, participants will choose lottery B until decision 5 (50% probability of drought) and then switch to A. They should change from Lottery B to Lottery A when expected value of A is higher than that of B. Extremely risk loving participants will choose lottery B at decision 9, while risk averse participants will choose lottery A in the first decision. Individuals are expected to choose Lottery B for the first few decisions before switching to lottery A as the probability of drought increases. An individual's degree of risk/ ambiguity aversion is estimated by the point where they switch from the safe to the risky lottery.

Table 2.1: Payoffs for the experiment

Choice (tick)		Drought	Rain
	Adopt	4	6
	Do not adopt	0	10

Table 2.2: Expected values of the two lotteries and CRRA at switch point

	Probability of drought					
Decision	**Risk**	**Ambiguity**	**EV^A**	**EV^B**	**EV^A - EV^B**	**CRRA**
1	10%	5-15%	5.8	9.0	-3.2	0.81
2	20%	15-25%	5.6	8.0	-2.4	0.62
3	30%	25-35%	5.4	7.0	-1.6	0.43
4	40%	35-45%	5.2	6.0	-0.8	0.22
5	50%	45-55%	5.0	5.0	0.0	0.00
6	60%	55-65%	4.8	4.0	0.8	-0.26
7	70%	65-75%	4.6	3.0	1.6	-0.57
8	80%	75-85%	4.4	2.0	2.4	-1.00
9	90%	85-95%	4.2	1.0	3.2	-1.71
10	100%	100%	4.0	0.0	4.0	-∞

- ***Choice of payoffs***

Payoffs of (4;6) for a decision to adopt and (0;10) for non-adoption represented the maize yield per hectare (Table 2.1).[19] We assumed the possibility of an excessive drought (e.g. the 2008 season where most farmers did not produce anything as their crops were destroyed), hence the payoff of 0 tonnes/hectare (t/ha). The risky gamble is such that farmers will lose all crops due to drought if they do not adopt the DT variety but they can get a high payoff of 10t/ha in the event of non-

[19] The payoffs were therefore output per hectare. Per hectare was used as a generic measure for the farmers to relate to the experiment. The actual land area was not used in the payoffs but we do acknowledge that the **actual farm size** and **area allocated to maize** does affect the farmers' adoption decisions hence we include these variables in the regression models. In addition, we also analyse what proportion of the land farmers would put under the new crop variety if they decide to adopt. The issue of crop diversification is not assessed in our study and may affect adoption decisions hence it can be a subject for subsequent research in technology adoption under risk/ambiguity.

occurrence of a drought. Farmers may be reluctant to adopt a new variety that they have never used before, hence they may choose not to adopt. There is a possibility of lower yields of 4 and 6 t/ha respectively if a farmer chooses to adopt under drought and a good rainy season respectively. The safe choice would therefore be to adopt. The risk averse farmers will take this choice even though there is a possibility of lower yields. There is need to note that there may be fixed costs associated with adoption. The fixed costs associated with adoption may perhaps include information costs associated with discovering, acquiring and adopting the new technology. We do believe this was captured by the differences in the payoffs. Subsequent studies can perhaps specify the fixed costs.

Over the past few years a number of seed companies in Zimbabwe have released DT maize varieties. Some local government agricultural officers/extension agents (who provide training and advice related to farming) we talked to, however did confirm that some of the drought tolerant varieties had lower yields compared to the other varieties. Yield levels were therefore used as the payoffs in the experiment. One seed company (SIRDC[20]) which recently introduced a drought tolerant variety stated that yields for trials done with smallholder farmers ranged from 1.5- 9ton/ha. Other seed companies produce varieties with yields ranging from 5 -13ton/ha under optimal conditions (low end of range is under little rain whilst high end is under normal rainfall). Using the potential yield levels that seed companies provided, we calculated the averages to use as payoffs.

Expected yields from drought tolerant varieties under good rainfall conditions are on average approximately 1.5 times more than under drought. Average optimal yields from a sample of the drought tolerant varieties on the market are approximately 6t/ha but the majority of smallholder farmers never reach that target due to inadequate inputs and other risk factors; therefore a yield of 4 was chosen which is about 1.5 times below the average optimum. But are smallholder farmers willing to adopt a variety they are not familiar with? Initial pilot experiments with smallholder farmers indicated that most farmers were willing to adopt a new variety at all probability levels of drought (sticking to safe choice); therefore we decided to ascertain their intensity of adoption (i.e. how much land they would allocate for the

[20] The Scientific and Industrial Research and Development Centre (SIRDC) was established in 1993 through an Act of Parliament in Zimbabwe with a mandate to provide technological solutions for sustainable development.

drought tolerant variety) for 10%, 50% and 100% chance of drought. This allows us to assess how farm size may affect proportion of land farmers allocate to the new maize variety. Section 2.5.2.3 provides detailed analysis on the proportion of land allocated to the new variety.

- ***Recruitment of participants and experiment administration***

Zimbabwe's agricultural land is divided into five agro ecological zones also known as natural regions (NRs) based on the rainfall patterns, soils, vegetation and other factors. Rainfall amount decreases from NR1 to NR5. The research was conducted in 4 districts in Zimbabwe namely Insiza (NR5), Shurugwi (NR4), Zvimba (NR3) and Bindura (NR2). Districts (shown in Appendix 2.2) were randomly selected from each of the natural regions. Since our experiment ascertains whether or not a participant will adopt a drought resistant variety given different levels of a drought occurring, 2 areas that normally have high rainfall and 2 that are drought prone were chosen to assess if there are any differences. Approximately 200 questionnaires were administered in the four states. From each district, a sample of representatives from each village was selected. Random selection of participants was done at the village level with the help of local government extension agents/officers (extension officers are always in contact with farmers and disseminate any information or training related to agriculture to them). Using lists of households provided by the extension agents on the ground, random households were picked for use in the study. Experiments were conducted with male and female smallholder farmers in rural Zimbabwe.

Recruitment of participants at the household level included female and male heads of households as well as one spouse per household for married couples. Experimental sessions were normally conducted between late morning and afternoon. Four research assistants were recruited to help with administration and two local officers in each area also helped with some of the logistics and questionnaire administration. Participant groups gathered at a central location (for example school or meeting hall) and the purpose of the meeting/ research and experiment was explained to them. At the end of the experiment, a questionnaire was completed on general household, individual characteristics and weather/climate change related information. This was in the form of structured face to face interviews with participants. Enumerators were trained beforehand on experiment and questionnaire administration.

A pilot study with 25 participants from one district was used to pre-test the experiment and questionnaire. This was done to assess understanding and ease of administration for both enumerators and respondents. A few changes were made to the tools after this exercise. The experiment and questionnaire were administered to the farmers using the local languages (Shona and Ndebele). Most of the smallholder farmers have some form of secondary/high school education so probability and chance were a bit easier to explain (results indicate that about 53% of the farmers did some secondary/high school education). Two main methods were used to explain the experiment. These included use of charts and local languages. For example to explain a 10% chance of rain participants were told that during a ten year period , if there is a drought in one of the seasons, then that would be a 10% probability of drought occurring. Weather forecast was used to explain unpredictability and uncertainty (rain/no rain) and other everyday examples like a team winning or losing a game were used. Charts, showing probability as shaded boxes were also used for explanation. It was emphasized that there were no right or wrong answers. After the experiment was explained to the farmers as a group, enumerators conducted the experiment with one individual farmer at a time. During the individual one on one session, farmers were asked if they understood the experiment and if not, instructions were repeated on a one to one basis. The last decision (explained later in the experimental design) that the farmers made was also used to test if they understood the experiment. In the last decision, the probability of drought was 100% hence farmers were expected to adopt. After conducting the experiment, payments were made as described below.

- ***Payment procedure***

At the end of the experiment, one decision was chosen at random for payment. Participants were told beforehand that one random decision would be chosen to determine their payoff and that this depended on their individual decisions. This method incentivises participants to consider each choice carefully and hence get truthful revelations from participants; the task becomes a binary option hence it would be in the participants' best interests to reveal the truth (Andersen et al. 2006; Harrison et al. 2010). To choose the payment decision, a participant was chosen at random to choose a number between 1 and 10 for the decisions. Once the decision was chosen, 10 small paper slips were put in a hat (e.g. if decision 2 was chosen, 2 of the slips had no rain shown on it and 8 had rain drawn on them). A participant was then asked to pick one paper from the hat at random to determine if the payoff would be from drought or rain. The participant was also asked to verify if there were 10 slips in the hat in front of all the participants. In some of the experiment sessions, to choose the payment decision a 10 sided die was rolled. For example, if decision 9 was chosen (with 90% chance of drought), to find out hypothetically if it would be a good rainy season / drought and hence determine payment, another die was rolled. If the 10 sided die was rolled and it showed a 0 then that would mean a rainy season, but if the die showed 1, 2, 3, 4, 5,6,7,8 or 9, then that would be a drought season. Initially, the researcher demonstrated the rolling of the die as an example but to determine actual payments, one participant was chosen. Farmers were paid using seed packs that had equivalent values of the payoffs. We used 2kg seed packs of maize which cost either \$3.00 or \$4.50 and cowpea seed packs which cost either \$0.50 or \$1.

2.4. Empirical Strategy

The study assumes expected utility theorem (EUT) and constant relative risk aversion utility (CRRA) following Harrison and Rutström (2008). The CRRA function is represented by:

$$U(x) = x^{1-r}/(1-r) \qquad (1)$$

where x = payoff/lottery prize and r = CRRA coefficient. $r = 0$ denotes a risk neutral participant, whilst a risk loving and risk averse participant will have $r < 0$ and $r > 0$ respectively. Our experiment has two possible lottery outcomes denoted by k , with probabilities, $p(k)$ which are specified by the experimenter. If we assume that EUT holds for the participants' choices, the expected utility which is the probability weighted utility of each outcome in each lottery (i) will be:

$$EU_i = \sum\nolimits_{k=1,2} [p(k) \times U(k) \qquad (2)$$

The choice of lottery A or B (adopt or do not adopt) depends on the following latent variable:

$$\nabla\, EU = \frac{EU_A - EU_B}{\mu} \qquad (3)$$

Where EU_A = expected utility from lottery A, EU_B= expected utility from lottery B and μ is the Fechner error parameter which accounts for participant behavioural errors, $\mu \sim N(O, \sigma^2)$. We use a cumulative normal distribution function, $\Phi(\nabla EU)$ such that, $(\nabla EU) = Pr(EU_A - EU_B) > 0$, measures the probability that lottery A is chosen over lottery B and $[1 - \Phi(\nabla \mathrm{EU})]$, measures the probability that lottery B is chosen. Hence, the log likelihood function which will be estimated is:

$$InL(r, \mu; y, \boldsymbol{X}) = \sum_i l_i = \sum_i [In\, \Phi(\nabla EU) \times \boldsymbol{I}\,(y_i = 1) + (In\big(1 - \Phi(\nabla EU)\big) \times \boldsymbol{I}(y_i = 0))] \quad (4)$$

Where $\boldsymbol{I}\,(.)$ is an indicator function, $y_i = 1(0)$ indicates choice of lottery A (B) in decision i and X = vector of individual characteristics e.g. sex, age, marital status and so forth.

MODEL-proportion of land allocated to drought tolerant variety

- There are 2 states of nature (drought or rain) i.e $k = (1{,}2)$ and participants are told the exact probability/range of probability of drought
- There are 2 crop varieties (drought tolerant and non-drought tolerant) associated with different payoffs depending on the state of nature such that:
  x_{dk} = payoff from drought tolerant variety (safe choice) in state k
  x_{rk} = payoff from non drought tolerant variety in state k
  Hence, $x_{r1} < x_{dk} < x_{r2}$ (payoffs were: $x_{d1} = \{4\}$ =, $x_{d2} = \{6\}$, $x_{r1} = \{0\}$, $x_{r2} = \{10\}$.
- There are two choices (adopt or do not adopt)- farmers were asked to choose whether or not to adopt a new drought tolerant maize variety
- And if they choose to adopt what proportion (Y) of their land they would put under the new crop variety at the different probability levels.

A double hurdle (DH) model was used to model the proportion of land allocated to the new DT variety. The model proposed by (Cragg 1971) is a generalised tobit model which allows two separate stochastic processes. In our case the farmer has to make two decisions. Decision 1: whether or not to adopt a new DT variety and decision 2: how much land to allocate to the new crop (level/intensity of adoption). A Tobit model assumes that these two decisions are jointly made. However, in a DH model, decisions are independent (conditional on observables) and may be uncorrelated. The proportion of land allocated to the drought tolerant variety is measured as a percentage. Therefore values are limited between 0 and 100% hence a left censored Tobit model could be used however for reasons outlined above, a DH model will be estimated. The model is defined as follows:

There is an adoption decision(D); such that $D = 1\ if\ D^* > 0$ (i.e. if farmer adopts) and 0 otherwise.

$$D^* = Z\alpha + \varepsilon \qquad (5)$$

where D^* is a latent variable for the desired demand for the new DT variety, Z is a vector of explanatory variables affecting the adopt/don't adopt decision, α is a vector of coefficients for the adopt/don't adopt decision and $\varepsilon \sim N(0, 1)$.

The intensity/level of adoption (Y) is represented by the following function:

$$Y^* = X\beta + \mu \qquad (6)$$

where Y^* is the unobserved latent variable, X is a vector of explanatory variables for the intensity of adoption, β is a vector of coefficients for the intensity of adoption and $\mu \sim N(0, \sigma^2)$ is the error term. The observed proportion of land allocated to the new drought tolerant variety (Y) will be equal to Y^* if $Y^* > 0$ and $D^* > 0$ and will equal 0 otherwise.

The model maximises the log of the following likelihood function:

$$L = \prod_0 \left[1 - \Phi(Z\alpha).1 - \Phi\left(\frac{X\beta}{\sigma}\right)\right] + \prod_1 \left[\Phi\left(\frac{Z\alpha}{\sigma}\right)\phi\left(\frac{Y - X\beta}{\sigma}\right)\right] \qquad (7)$$

Where $\Phi(.)$ and $\phi(.)$ are standard normal cumulative density function and standard normal probability density function, respectively. The DH model will incorporate the probit model in the first tier and truncated normal regression in the second. DH will be run for decision 1 only because at decisions 5 and 10 almost all farmers indicate that they will adopt.

2.5. Results

2.5.1. Summary statistics

The research was conducted with 200 farmers (49.5% were female). Tables 2.3 and 2.4 give a summary of characteristics of the households and respondents disaggregated by sex. The average household size was 6 and just over half of them were children. More than three quarters of the respondents were married whilst around 19.5% were widowed. In terms of education, most of the participants had attended at least primary school with around 60.4% and 44.4% of the males and females, respectively having attended secondary school. Summary statistics disaggregated by district and gender are presented in Appendix 2.3.

Since the context of our study is *drought*, we asked farmers about the weather changes they have been experiencing over the past few years as this can influence their decision making. There are clear differences in the weather patterns being experienced by the farmers in the different districts (Table 2.4b) and this can adversely affect farmers' production and decision making. Just close to half of all the farmers felt that the temperatures had increased over the past years. Sixty-two percent of the farmers in Bindura (one of the districts that normally receive above normal rainfall) indicated increased mid-season dry spells. Mid-season dry spells can significantly reduce yields depending on the stage of crop development and period of time they occur; if they occur for at least 3 weeks, it can lead to a total maize loss or significant reduction in grain yield levels (Edmeades et al. 1996). Around 35% of all farmers reported an increase in the frequency of droughts. More than three quarters of farmers in Insiza (dry district) said there was an increase in the frequency of droughts compared to only 4% in Bindura (wet district). Winters are getting colder and rains are starting later than they used to for just over half of the farmers.

Table 2.3: Summary statistics

		Total (n=200)	Male (n=101)	Female (n=99)
		%	%	%
District	Bindura	25.0	24.7	25.2
	Insiza	19.5	17.8	21.2
	Shurugwi	27.0	28.7	25.2
	Zvimba	28.5	28.7	28.3
Education	None	1.5	1.0	2.0
	Primary	41.0	31.7	50.5
	Secondary	52.5	60.4	44.4
	Tertiary	5.0	6.9	3.0
Marital status	Married	75.5	93.1	57.6
	Widowed	19.5	3.9	35.3
	Divorced	3.5	2.0	5.0
	Single	1.5	1.0	2.0
Main source of income	remittances	14.5	13.9	15.1
	crop sales	48.5	49.5	47.5
	casual labour	8.5	11.9	5.1
	artisan/petty trade	9.0	4.9	13.1
	gold panning/mining	6.5	6.9	6.1
	livestock sales	5.5	7.9	3.0
	medium/large business	0.5	1.0	0.0
	formal salary/pension	3.0	3.9	2.0
	vegetable sales	4.0	0.0	8.1
Contact with extension agent (yes)		83.0	79.2	86.9
Member of association (yes)		64.5	55.4	73.7
Aware of DT varieties (yes)		76.9	65.3	88.8
Access to mobile phone (yes)		91.2	91.8	90.5
Own radio/ TV		84.3	88.9	79.8

Table 2.4(a): Summary statistics for continuous variables

	n	mean	s.d	min	Max
Age of respondent (all)	195	51.7	14.5	25	91
Age (male)	99	53.3	15.8	25	91
Age (female)	96	50.2	50.2	27	85
Age - Bindura	47	43.8	13.1	27	72
Insiza	38	56.1	14.9	28	80
Shurugwi	49	53.9	15.9	25	91
Zvimba	51	55.7	11.3	27	85
Total family size	200	6.0	2.6	1	17
Number of children in household	200	3.3	1.7	0	10
Total land (ha)	200	3.6	2.1	0.5	12
Area under maize (ha)	193	1.2	0.96	0	4.5
Total cultivated land (ha)	200	1.4	2.4	0.4	8

Table 2.4(b): Responses on ways in which climate has changed over past 10 years (%)

	all	Bindura	Insiza	Shurugwi	Zvimba
increased temperature	46.5	30.0	59.0	48.1	50.9
mid season dry spells	49.5	62.0	15.4	48.1	45.6
frequent droughts	34.5	4.0	76.9	37.0	29.8
frequent frost	14.0	2.0	2.6	11.1	61.4
decreased winter temperature	53.5	72.0	7.7	48.1	73.7
early onset of rains	20.5	32.0	33.3	9.3	12.3
late onset of rains	55.5	52.0	20.5	59.3	78.9

2.5.2. Experimental results

This section presents experimental results using 3 main attributes: (1) Adoption at all levels/decisions, (2) Number of safe choices – which will be our measure of risk/ambiguity aversion, and (3) Proportion of land allocated to new variety. For each attribute, descriptive statistics will be given first, followed by regression results.

Ninety-eight farmers were presented with ambiguous choices whilst 102 were presented with the risk lotteries. Ten of the respondents were inconsistent (i.e. they would revert back to risky option B after choosing or switching to the safe option A). Half of the inconsistent farmers, switched to option B at decision 5 and then back to option A: at decision 5, it was equally likely for it to rain or for a drought to occur. Some of the inconsistent participants may not have understood the experimental instructions. The latter were excluded from analyses.

2.5.2.1 Adoption at all levels/decisions[21]

About 65% of the participants chose the safe option (adopt) for all decisions (note

[21] This analysis on adoption is important because it allows us to understand why on average most of the farmers were not behaving ‘rationally’. We expected the majority of farmers to be risk averse (informed by literature which has done similar research) but instead most of the farmers in our sample where *extremely averse*- and chose the safe option (adoption) at all risk levels. The subsequent analysis in this section allows us to model this and determine the socioeconomic characteristics of farmers who were adopting at all risk levels.

that this part of the analysis includes all farmers). This indicates extreme risk/ambiguity aversion on the part of these farmers. In general, results indicate that smallholder farmers are reluctant to adopt new technologies that they have little or no experience using. In our experiment, adoption was the safe choice given different probabilities of a drought occurring hence farmers chose to adopt. This result can be attributed to the way our experiment was framed. A control treatment can be included in subsequent studies, where non adoption is the safe choice, in order to test for framing effects.

Tables 2.5 and 2.6 show results of different characteristics for participants who adopted at all levels and those who did not. Among the farmers who chose to adopt at all levels, around 51.4 % were presented with the risk treatment whilst the rest were presented with the ambiguity. Results indicate that, 66.7% of the farmers who were presented with the risk treatment choose to adopt at all levels compared to 63.3% for the ambiguous one (Table 2.6). The number of farmers who choose to adopt at all levels is equally divided between the males and females. Amongst the men, about 64.4 % choose to adopt at all levels. Around 56.4% of the widowed participants choose to adopt at all levels.

Table 2.5: Comparison of farmers who adopted at all levels vs. those who did not (%)

		Adopt all (n =130)	**Do not adopt all (n=70)**	**chi**	**p**
Treatment	Risk	51.4	47.7	0.254	0.614
	Ambiguity	48.6	52.3		
Sex	Male	50.0	51.4	0.037	0.847
	Female	50.0	48.6		
Marital status	Married	77.7	71.4	1.632	0.652
	Widowed	16.9	24.3		
	Divorced	3.8	2.9		
	Single	1.5	1.4		
Education level	None	1.5	1.4	3.144	0.370
	Primary	43.1	37.1		
	Secondary	52.3	52.9		
	Tertiary	3.1	8.6		
District	Bindura	19.2	35.7	9.604	0.022
	Insiza	22.3	14.3		
	Shurugwi	31.5	18.6		
	Zvimba	26.9	31.4		
Member of association	Yes	71.5	51.4	8.036	0.005
Aware of DT varieties	Yes	77.7	75.4	0.138	0.711
Access to mobile phone	Yes	92.8	88.2	1.143	0.285
Own radio/ TV	Yes	81.2	90.0	2.624	0.105

Table 2.6: Percent who choose to adopt at all levels for each characteristic

Characteristic		n	Adopt all (%)
Treatment	Risk	98	66.7
	Ambiguity	102	63.3
Sex	Male	101	64.4
	Female	99	65.7
Marital status	Married	151	66.9
	Widowed	39	56.4
	Divorced	7	71.4
	Single	3	66.7
Education level	None	3	66.7
	Primary	82	68.3
	Secondary	105	64.8
	Tertiary	10	40.0
District	Bindura	50	50.0
	Insiza	39	74.4
	Shurugwi	54	75.9
	Zvimba	57	61.4
Member of association	Yes	129	72.1
	No	71	52.1
Aware of DT varieties	Yes	153	63.0
	No	46	66.0
Access to mobile phone	Yes	176	65.9
	No	17	52.9
Own radio/ TV	Yes	167	62.3
	No	31	77.4

Over half of the participants who chose to adopt at all levels were from the normally ‘dry’ districts (Insiza and Shurugwi). Close to three-quarters of farmers from these dry districts choose to adopt at all levels. There is a significant association between membership to an association and choosing to adopt at all levels at the 1% level of significance. Around 72% of the farmers who indicated they were a member of an association adopted at all levels.

Probit regression with adoption at all levels as dependent variable

Probit regression models were run to assess the determinants of adopting at all levels. The dependent variable was a dummy variable (1= if farmers adopted at all levels and 0 if they did not adopt at all levels). The independent variables included different characteristics of the respondents and their households (explanations of variables used in all regression analyses are given in Table 2.7).

Table 2.7: Variables used in regression analyses

Variables	Description
female	1= female, 0=male
age	age of respondent (yrs)
married	1= married, 0=widowed/single/divorced
education	1= primary, 0= secondary/tertiary
family size	household size
children	number of children in household
total land	total land owned (ha)
maize area	maize area cultivated last season (ha)
extension	1= had contact with extension agent
association	1= is a member of an association/ farmer group
district	1= dry districts(Insiza and Shurugwi) 0= wet districts(Bindura and Zvimba)
DT aware	1= aware of drought tolerant (DT) varieties
radio/TV	1= own radio/TV, 0 = otherwise
mobile phone	1= have access to mobile phone, 0 = otherwise
treatment	1= presented with risk, 0 = presented with ambiguity

Marginal effects were computed to measure the probability of adopting at all levels. Results are shown in Tables 2.8(a) and (b). Significant determinants for all famers include: married, total land, maize area, association and district. Individual respondents' characteristics such as age, sex and education had no significant effect on adopting at all levels. Married farmers were 18.2% more likely to adopt at the 10% level of significance on average. There was a positive relationship between whether or not a participant adopted at all levels and total land owned. On average, one more hectare of land increased the likelihood of adoption at all levels by 4.4% and this is significant at the 10% level. This positive association might indicate that owning land is an incentive to adopt: these farmers have more land at their disposal and can diversify into another crop variety. Total land was used as a proxy for wealth thus indicating that the wealthier farmers are more likely to adopt at all levels and put part of their land under the new crop. Farmers who put more land under maize in the past season were on average 8.2% less likely to adopt at all levels. This maybe because these farmers made their decisions based on last season's (2010/11) experience which was a relatively good rainy season. If that is the case, farmers might choose not to adopt at the lower probability levels.

Farmers who are a member of an association were more likely to adopt at all levels. Through this communication and interaction, farmers might encourage each other to try new technologies. This is significant at the 1% level and the probability of adopting at all levels is on average 29% higher for farmers who are members of an association. As expected, farmers in the ‘dry’ districts were more likely to adopt at all levels compared to those in areas that normally receive normal to above normal rainfall. Since they are more prone to drought, they chose to be safe and adopt even at very low probabilities of a drought occurring. This relationship is significant at the 1% level with farmers in the dry districts 24.7% more likely to adopt at all levels on average. Ownership of radio/TV had a negative significant impact on adoption at all levels at the 10% level. Whether or not farmers were presented with the risk or ambiguity treatment did not have a significant impact on adoption at all level for all farmers.

Probit regressions were also run for different groups of participants, based on sex of respondents, treatment presented to participants (risk/ambiguity) marital status and district, to determine if there were differences in factors determining adoption at all levels. For female farmers, membership of an association, ownership of radio/TV and awareness of other DT varieties, are significant at the 1% level. Membership of an association increases the probability of adoption at all levels by 48.9% on average. Females who indicated that they are aware of other DT varieties are on average 32.7% less likely to adopt at all levels whilst ownership of a radio/TV decreases adoption at all levels by 33.6% on average. If farmers are aware of DT varieties, they are probably already using those varieties. If that is the case they possibly may not adopt at all levels. Another reason could be that the DT varieties they are using, are working for them and they don’t want to try any new ones at the very low probabilities of drought. Male participants have different determinants from their female counterparts. Total land is a significant factor for the males and age also becomes a determinant. For an average male farmer, an extra year and hectare of land increases the probability of adoption by 0.7% and 5.1% respectively. Men are normally the landowners and this is rooted in the cultural and patriarchal nature of Zimbabwe’s land system.

Farmers from dry districts are more likely to adopt at all levels for both risk and ambiguity. Mobile phone access increased the probability of adopting at all levels by 53.2% on average for those presented with risk. However, for those presented with the ambiguity treatment, mobile phone access has a negative impact. When disaggregated by marital status the age of the respondent also becomes a determinant of adopting at all levels for both the married and single farmers. An additional year from the average decreases the probability of adopting at all levels for single parents by 1.7% whilst it increases the probability by 0.7% for married farmers. The older married farmers are more likely to adopt at all levels whilst the younger single parents were less likely to do so. The other determining factors for married famers are total land and district as is the case with all farmers. For single parents, membership of an association increases the probability of adopting at all level by 79.1% on average and radio/TV ownership decreases adoption at all levels by 52.1%.

Regressions run for the districts show that farmers from the ‘wet’ districts are less likely to adopt at all levels if they indicated that they were aware of other DT varieties. Analysis of the individual ‘wet’ districts shows no significant determinants for Bindura, whilst for Zvimba, in addition to the variables that are significant for all farmers; sex, age and marital status become positively significant. Females, the older and married respondents in Zvimba are on average more likely to adopt at all levels. For the individual dry districts, the number of children is a significant determinant with a positive relationship for Shurugwi, whilst for Insiza one more extra child decreases the probability of adopting at all levels by 17.6% on average.

Table 2.8(a): Determinants of adopting at all levels using probit model

	all		**female**		**male**		**risk**		**ambiguity**		**married**		**single**	
	coef	ME	coef	ME	coef	ME	coef	ME	coef	ME	coef	ME	coef	ME
female	0.232	0.085					0.627	0.229	0.099	0.035	0.323	0.114	0.117	0.044
age	0.004	0.002	-0.011	-0.004	0.019	**0.007***	0.010	0.004	0.000	0.000	0.018	**0.007***	-0.047	**-0.017***
married	0.479	**0.182***	0.566	0.202	-0.177	-0.063	0.879	**0.338***	0.217	0.079				
education	0.086	0.032	0.339	0.121	-0.250	-0.093	-0.170	-0.064	0.259	0.091	0.129	0.047	-1.051	**-0.354***
family size	0.003	0.001	0.046	0.016	0.054	0.020	0.029	0.011	0.004	0.001	-0.007	-0.002	0.030	0.011
child	0.057	0.021	-0.044	-0.016	0.051	0.019	-0.057	-0.022	0.101	0.036	0.008	0.003	0.450	0.167
total land	0.118	0.044**	0.053	0.019	0.138	**0.051***	0.184	**0.069***	0.069	0.024	0.123	**0.045***	0.515	0.191*
maize area	-0.222	**-0.082***	0.026	0.009	-0.366	-0.134	-0.243	-0.091	-0.352	-0.124	-0.203	-0.074	-0.278	-0.103
extension	-0.025	-0.009	0.566	0.215	-0.027	-0.010	-0.072	-0.027	-0.102	-0.035	-0.172	-0.061	-0.445	-0.154
association	0.778	**0.290*****	1.337	**0.489*****	0.302	0.111	0.376	0.142	1.104	**0.395*****	0.403	0.147	2.746	**0.791*****
district	0.688	**0.247*****	0.172	0.061	0.940	**0.332*****	0.632	**0.232***	0.753	**0.257****	0.671	**0.237****	0.211	0.078
treatment	-0.076	-0.028	-0.009	-0.003	-0.332	-0.121					0.031	0.011	-0.895	-0.330
DT aware	-0.364	-0.128	-1.332	**-0.327*****	-0.074	-0.027	0.060	0.023	-0.736	**-0.237****	0.155	0.057		
radio/TV	-0.554	**-0.184***	-1.283	**-0.336*****	0.209	0.079	-0.746	**-0.242***	-0.553	-0.173	-0.339	-0.115	-2.023	**-0.521*****
mobile	0.144	0.054	-0.177	-0.060	0.487	0.188	1.496	**0.532*****	-1.132	**-0.284****	0.746	0.289	0.376	0.145
constant	-0.859		1.017		-2.026		-2.637		1.079		-1.758		0.479	

*** p<0.01, ** p<0.05, * p<0.1
ME= marginal effects

Table 2.8(b): Determinants of adopting at all levels using probit model by district

	wet		**dry**		**Bindura**		**Insiza**		**Shurugwi**		**Zvimba**	
	coef	ME	coef	ME	coef	ME	coef	ME	coef	ME	coef	ME
female	0.538	0.211	-0.135	-0.039	13.050	1.000	0.346	0.054	-1.070	-0.268	1.761	**0.517*****
age	0.016	0.006	0.003	0.001	-0.016	-0.005	-0.001	0.000	0.014	0.003	0.048	**0.016****
married	0.279	0.111	0.681	0.219	-1.313	-0.459	1.771	0.476	0.316	0.077	2.006	**0.673*****
education	0.361	0.142	-0.091	-0.026	-1.431	-0.234	-1.176	-0.146	0.417	0.090	0.655	0.220
family size	0.139	0.055	-0.075	-0.022	0.003	0.001	0.483	0.074	-0.358	**-0.081***	-0.039	-0.012
child	-0.058	-0.023	0.185	0.053	0.231	0.067	-1.147	**-0.176****	0.764	**0.173****	0.339	0.109
total land	0.124	0.049	0.046	0.013	-0.103	-0.030	-0.099	-0.015	-0.101	-0.023	0.381	**0.123****
maize area	-0.396	-0.158	-0.035	-0.010	0.271	0.079	-0.508	-0.078	0.075	0.017	-0.946	**-0.305***
extension	0.050	0.020	0.369	0.120	0.943	0.194					0.106	0.034
association	0.450	0.178	0.992	**0.320*****	0.639	0.182	2.413	**0.451****	1.494	**0.476***	1.817	**0.585*****
treatment	-0.123	-0.049	0.020	0.006	-0.893	-0.240	1.477	0.243	-0.316	-0.072	-0.088	-0.028
DT aware	-0.631	**-0.244***	-0.163	-0.045	-13.790	-1.000			0.333	0.082	-0.608	-0.177
radio/TV	-0.654	-0.243	-0.655	-0.158	-6.958	-0.944	0.185	0.031			0.957	0.355
mobile	0.411	0.162	-0.247	-0.065	-1.673	-0.592			-0.560	-0.097	-0.141	-0.044
constant	-1.580		-0.209		9.211		0.849		-0.414		-7.737	

*** p<0.01, ** p<0.05, * p<0.1
ME= marginal effects

2.5.2.2 Number of safe choices

Table 2.9 shows the total number of safe choices the participants make for the risk and ambiguity treatments. Following Holt and Laury (2002), the participants are categorised into risk/ambiguity aversion classes depending on the number of safe choices they make. Just over three quarters (75.7%) of all the farmers are in the highly to extremely risk/ambiguity averse category. None of the females are in the neutral or risk/ambiguity loving category whilst about 4% of the male farmers are neutral. About 74% of the males are extremely risk averse compared to 78% of the female farmers. The number of safe choices between the participants shown for different treatments indicates that around 76.5 % of those shown the ambiguity treatment are extremely averse, whilst for those shown the risk treatment; around 74.5% are risk averse.

Table 2.9: Total number of safe choices by experiment treatment

Number of safe choices	**Percent**				**Percent (of total)**	**Risk/ambiguity aversion class**
	Ambiguity	Risk	Male	Female		
5	-	4.1	4.2	-	2.1	Neutral
6	3.2	4.1	6.3	1.1	3.7	Averse
7	7.5	7.2	5.2	9.6	7.3	Very Averse
8	10.8	11.3	10.4	11.7	11.1	Highly Averse
9	10.8	4.1	7.3	7.5	7.3	Extremely Averse
10	67.8	69.1	66.7	70.2	68.4	Extremely Averse

Figures 2.3(a)-(d) show the number of farmers choosing the safe choice as the experiment progressed i.e. for each of the decisions. There are significant differences in the total number of safe choices between the male and female participants with the later being significantly higher ($t=-1.36$, $p<0.1$). This is also the case between male and female participants shown the risk treatment ($t=-1.60$, $p<0.1$). T-Tests show significant differences between the average total number of safe choices between farmers from the dry districts and those from the wet districts. As expected, farmers from the dry districts chose more safe choices than those from the wet districts ($t=-2.67$, $p<0.01$). There are no significant differences in the total number of safe choices by treatment (risk vs. ambiguity: $t=0.94$, $p= 0.35$) and there are no significant gender differences for participants shown the ambiguity treatment ($t= -0.15$, $p=0.88$).

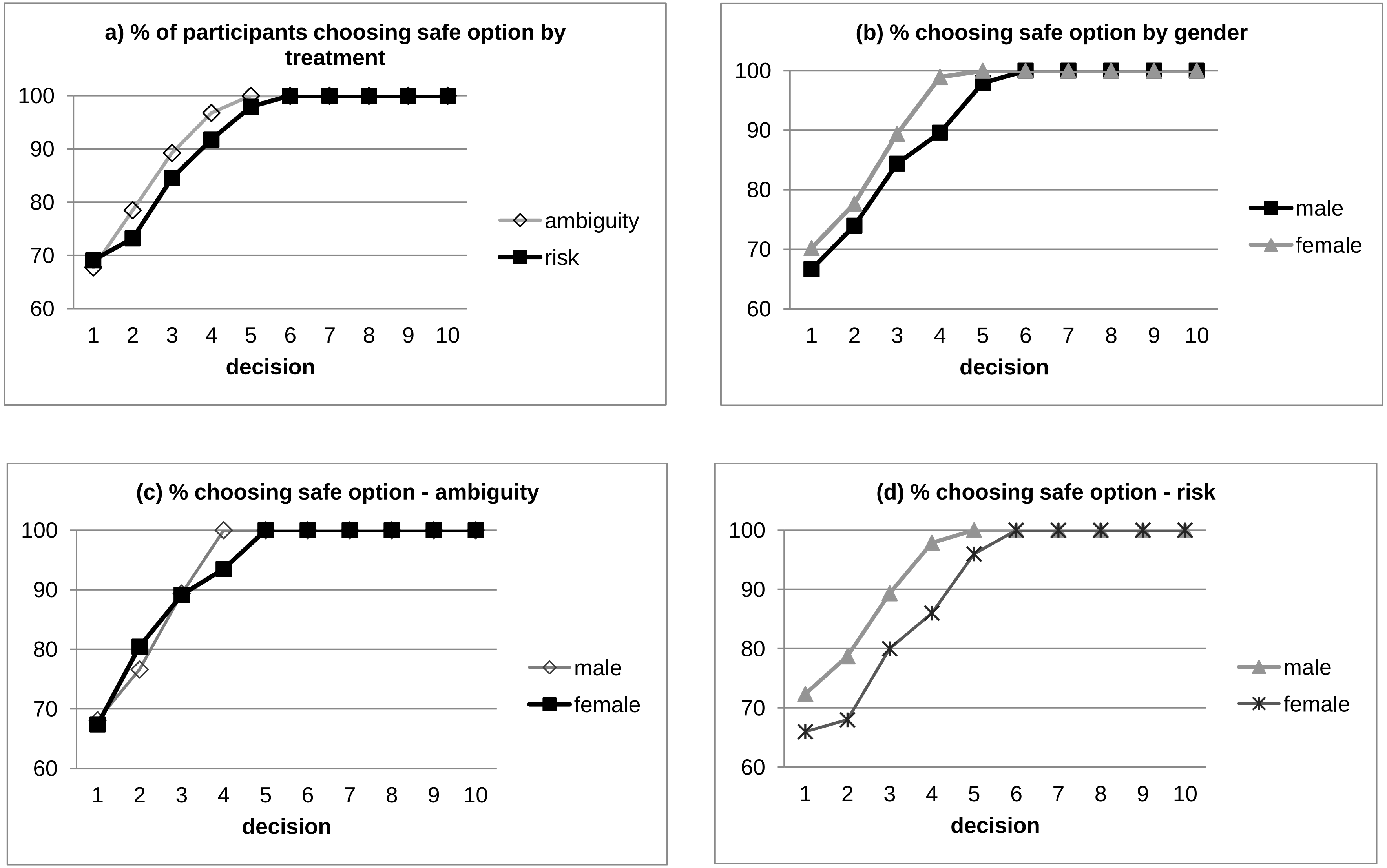


Figure 2.3 (a)-(d): Percent choosing safe option by decision, treatment and gender

Using the number of safe choices as a measure of risk aversion, we ran ordered probit regressions to assess the determinants of risk/ambiguity aversion[22]. The dependent variable is the total number of safe choices an individual farmer could choose hence it is an ordinal variable which takes the values 0 to 10. Harrison et al. (2005) suggests why an ordered probit model would be appropriate[23]. Results are reported in Tables 2.10(a) and 2.10(b).

The factors affecting risk/ambiguity aversion for all farmers are: total land, membership to an association, district, ownership of radio/TV and access to a mobile phone. All of these have a positive relationship with risk/ambiguity aversion except ownership of radio/TV which has a negative one. Total land was used as a measure of wealth and results indicate wealthier individuals are more risk averse: these results are consistent with (Ihli et al. 2013, Wik et al. 2004). Ownership of a radio/TV, which can also indicate wealth, however, has an inverse relationship with risk aversion. Farmers who own a radio/TV are less risk averse.

- As expected farmers from the dry districts are significantly more averse compared to those from the wet ones since they experience droughts or dry seasons more frequently. Farmers who are members of an association are more averse and more likely to adopt at low risk levels of a drought occurring. Associations or farmer groups are social networks where farmers exchange information related to farming and other issues. Our experiment was designed to measure attitudes related to adoption of a drought tolerant variety which is a way of reducing weather and climate related risks, therefore, farmers who are part of groups and might discuss reducing their exposure to these risks and are more likely to choose the safe option. Farmers who have access to a mobile phone are more averse. A mobile phone just like membership of an association is a form of a communication and information exchange medium; hence the positive relationship would be expected.
- There are differences in the factors determining ambiguity aversion and risk aversion. Wealth factors determine risk aversion whilst geographical location and other non wealth related factors significantly affect ambiguity aversion. For

[22] Interval regression models which are an extension OLS were also run for comparison sake. The results are reported in appendix 2.4. The dependent variable in this case is the range between the upper and lower bounds of the CRRA. Factors affecting risk/ambiguity preferences are the same for almost all categories.
[23] They indicate that an ordered probit model recognizes the natural ordering of the 10 decisions that participants have to make in the experiment, and that these decisions are not ten independent observations for each individual. Another advantage is that, 'we can remain agnostic about the functional form of the utility function.'

participants shown the risk treatment, total land and mobile phone access have a positive relationship with risk aversion whilst radio/TV ownership has a negative relationship. Significant factors for ambiguity aversion are membership of an association, district and DT awareness. The later has a negative relationship. When the risk is known, results indicate wealth is more significant in technology adoption decisions. Ambiguity was presented as a range of probabilities of a drought occurring, and farmers in dry districts are more ambiguity averse and are more likely to choose the safe choice as there is more variability in the information provided.

Table 2.10(a): Ordered probit regression with total number of safe choices as dependent variable

	all	risk	ambiguity	female	male	married	single
female	0.290	0.440	0.426			0.268	0.646
	(0.235)	(0.378)	(0.367)			(0.278)	(0.931)
age	-0.008	-0.008	-0.011	-0.023	0.005	0.004	-0.016
	(0.008)	(0.015)	(0.011)	(0.017)	(0.010)	(0.010)	(0.022)
married	0.273	0.400	0.278	0.271	0.108		
	(0.270)	(0.445)	(0.369)	(0.372)	(0.525)		
education	0.017	-0.120	0.042	0.005	-0.187	0.054	**-1.471****
	(0.229)	(0.367)	(0.342)	(0.365)	(0.338)	(0.274)	(0.738)
family size	0.047	0.014	0.084	0.056	0.132	0.102	-0.135
	(0.075)	(0.103)	(0.120)	(0.143)	(0.115)	(0.010)	(0.263)
children	-0.046	-0.056	-0.110	-0.280	-0.052	-0.123	0.362
	(0.102)	(0.152)	(0.164)	(0.192)	(0.148)	(0.123)	(0.397)
total land	**0.103***	**0.237****	0.025	0.090	0.097	0.084	0.028
	(0.057)	(0.109)	(0.078)	(0.112)	(0.071)	(0.062)	(0.247)
maize area	-0.130	-0.104	-0.209	0.058	-0.203	-0.074	0.117
	(0.123)	(0.193)	(0.214)	(0.199)	(0.240)	(0.145)	(0.377)
extension	-0.306	-0.376	-0.597	0.661	-0.154	-0.465	0.765
	(0.315)	(0.489)	(0.490)	(0.694)	(0.429)	(0.400)	(0.814)
association	**0.702*****	0.428	**0.882*****	**1.068*****	0.326	0.376	1.154
	(0.217)	(0.346)	(0.317)	(0.345)	(0.319)	(0.263)	(0.753)
district	**0.674*****	0.343	**1.127*****	**0.782***	0.430	**0.473***	0.755
	(0.245)	(0.355)	(0.407)	(0.461)	(0.354)	(0.287)	(0.816)
treatment	-0.260			-0.174	**-0.511***	-0.278	0.532
	(0.207)			(0.332)	(0.298)	(0.246)	(0.582)
DT aware	-0.255	0.238	**-0.875****	**-1.420***	0.186	0.186	-6.665
	(0.257)	(0.383)	(0.395)	(0.757)	(0.337)	(0.305)	(370.5)
radio/TV	**-0.636***	**-1.081****	-0.306	-0.827	-0.176	-0.576	-1.219
	(0.340)	(0.545)	(0.563)	(0.554)	(0.484)	(0.419)	(1.299)
mobile	0.451	**1.357****	-0.315	-0.576	**0.939***	**1.009****	-6.154
	(0.354)	(0.556)	(0.629)	(0.797)	(0.497)	(0.424)	(507.1)

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

DT awareness has a negative relationship with ambiguity aversion hence farmers who indicated they were aware of other DT varieties are less ambiguity averse. This can either indicate that farmers are already using these DT varieties and therefore will only adopt at the higher probability levels.

Members of associations are also more ambiguity averse. These results indicate the need to assess both risk and ambiguity attitudes.

- Female and male farmers also have different socio-economic factors affecting their risk/ambiguity attitudes. For female farmers, membership of an association is positively significant at the 1% level whilst that is not the case for male farmers. This might indicate that more of the female farmers are members of associations/groups that actually discuss farming related issues. Most farmer groups are differentiated by gender. As discussed earlier, women are relatively concerned more about household welfare especially food consumption hence they might discuss more about these issues within their groups. In addition, female farmers in dry districts are more averse compared to their counterparts in wet districts and female farmers who indicated they are aware of other DT varieties, are less averse. For the male farmers, treatment and mobile phone access have a significant impact on attitudes. Males presented with the ambiguity treatment and those with access to mobile phones are more averse at the 10 and 1% levels respectively.

Table 2.10(b): Ordered probit regression by district

	dry	wet	Bindura	Insiza	Shurugwi	Zvimba
female	0.180	0.460	1.370	-1.011	-0.225	**1.843** **
	(0.490)	(0.316)	(0.888)	(1.142)	(0.908)	(0.842)
age	-0.006	-9.88e-05	-0.032	-0.012	0.003	0.027
	(0.015)	(0.012)	(0.021)	(0.030)	(0.032)	(0.023)
married	0.353	0.154	**-1.633** **	1.111	-0.677	**1.818** **
	(0.538)	(0.349)	(0.729)	(1.022)	(1.211)	(0.830)
education	-0.246	0.349	**-1.642** **	-0.522	-0.395	0.734
	(0.455)	(0.289)	(0.764)	(0.897)	(1.084)	(0.599)
family size	-0.033	0.229	**0.844** **	0.095	-0.093	-0.109
	(0.095)	(0.146)	(0.376)	(0.288)	(0.210)	(0.248)
children	0.093	-0.252	**-0.983** **	**-1.014** **	0.343	0.362
	(0.170)	(0.160)	(0.411)	(0.432)	(0.382)	(0.281)
total land	0.051	0.101	0.019	0.010	-0.209	**0.265** *
	(0.113)	(0.071)	(0.161)	(0.397)	(0.253)	(0.150)
maize area	-0.021	-0.165	0.636	0.153	0.511	-0.613
	(0.200)	(0.253)	(0.583)	(0.430)	(0.600)	(0.656)
extension	-4.971	-0.344	**-1.427** *		-1.396	-0.032
	(966.7)	(0.346)	(0.787)		(2,648)	(0.616)
association	**1.053** ***	0.077	0.156	**2.596** ***	**1.834** **	**1.400** *
	(0.352)	(0.313)	(0.518)	(0.915)	(0.838)	(0.721)
treatment	-0.213	-0.155	-0.547	**1.663** **	-0.805	0.183
	(0.347)	(0.285)	(0.517)	(0.739)	(0.782)	(0.491)
DT aware	0.022	-0.459	-0.861	-7.241	-0.454	-0.751
	(0.525)	(0.327)	(0.728)	(907.1)	(0.878)	(0.618)
radio/TV	-0.512	-0.772	**-3.108** **	0.770	-4.903	0.582
	(0.546)	(0.529)	(1.445)	(1.299)	(716.0)	(1.192)
mobile	-4.234	**1.233** ***	**2.679** **	-2.812	-3.401	0.830
	(429.0)	(0.463)	(1.069)	(616.8)	(1,091)	(0.709)

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

- For married farmers only, mobile phone ownership and district are significant at the 5 and 10% levels respectively and increase risk/ ambiguity aversion. For single parents, education is the only negatively significant variable. This suggests that the more educated single farmers are less risk averse compared to the more educated single farmers. Most of the single farmers are divorced women hence they are the household heads. In their study of risk aversion and technology choice in Ethiopia, Knight, Weir and Woldehanna (2003) found that the education of the household head decreased risk aversion and schooling encouraged innovation.
- If the regressions are run after disaggregating by district, farmers from dry districts who are members of an association/farmer group are more averse and farmers from wet districts who have access to a mobile phone are more averse. Associations therefore, play an important role in dry districts. Individual districts also have different determinants for risk/ambiguity aversion.
- Female farmers and married participants in Zvimba are more averse compared to their male and single parent counterparts. However, in Bindura which is the other wet district, married farmers are less risk averse. This can be attributed to the ages of the farmers in the two districts. In Bindura, the married farmers are on average younger (age=43.5) than the married farmers in Zvimba whose mean age = 55.2. In addition, education, number of children, family size, extension, radio/TV ownership and mobile phone access, are significant factors in Bindura. The more educated farmers, those with more children and farmers who own a radio/TV are likely to be less risk/ambiguity averse, whereas farmers in Bindura with bigger households and have access to a mobile phone are more risk averse. For both the dry districts, membership of an association is significant. Farmers who are members of an association in Insiza and Shurugwi were more averse. The experimental treatment is significant for the Insiza farmers; those presented with the risk treatment choose more safe options. These results indicate the need to disaggregate analysis by geographical location as there maybe underlying cultural and social factors affecting decision making.

2.5.2.3. Proportion of land allocated to new maize variety

Farmers, who indicated that they were willing to adopt the new DT variety, were also asked the proportion of their land area they would propose to put under the new DT crop (intensity of adoption). Responses were asked at decisions 1, 5 and 10. Figure 2.4 shows that as expected, the proposed proportion of land at all decisions for farmers presented with the ambiguity treatment is higher than for those shown the risk treatment.

Figure 2.4: Proposed mean proportion of land allocated to new DT variety (%)

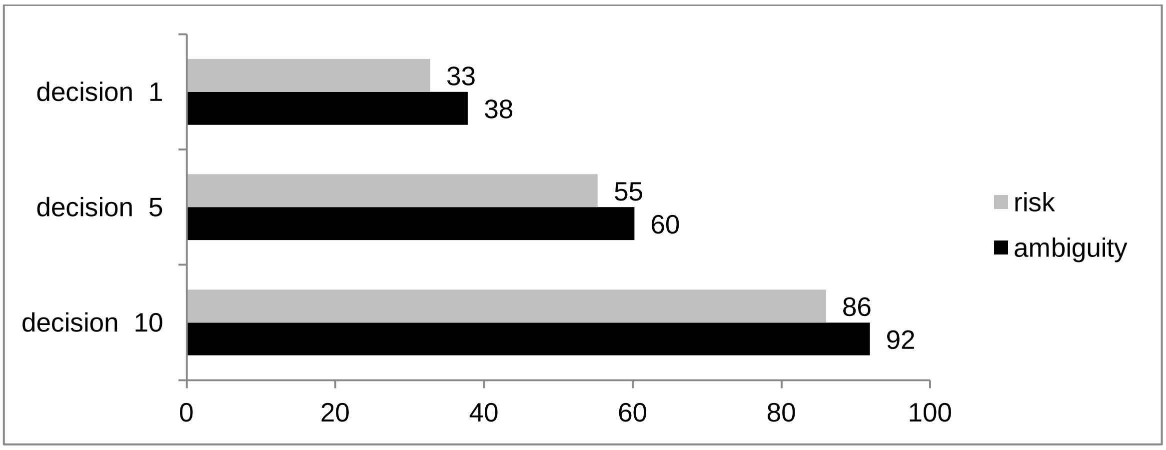


Table 2.11: Proportion of land allocated to new variety by treatment

		n	average (%)	min	max	t-value
decision 1	ambiguity	53	37.8	8	100	1.08
	risk	59	32.8	4	100	
decision 5	ambiguity	83	60.2	25	100	1.57*
	risk	82	55.3	14	100	
decision 10	ambiguity	82	91.9	40	100	1.98**
	risk	82	86.0	12	100	

Table 2.12: Proportion of land allocated to new variety by gender

		male		female		t-value	p
		average (%)	n	average (%)	n		
decision 1	ambiguity	39.8	26	35.9	27	0.56	0.580
	risk	29.6	27	35.4	32	-0.92	0.362
decision 5	ambiguity	63.5	40	57.2	43	1.46	0.149
	risk	54.7	40	55.8	42	-0.25	0.805
decision 10	ambiguity	91.0	40	92.7	42	-0.48	0.634
	risk	86.6	40	85.4	42	0.26	0.794

The farmers presented with risk propose to put on average just over half of their land under the new DT crop at 50% chance of drought. T-Tests (Table 2.11) indicate that the mean land farmers would allocate to the new DT variety at decisions 5 (50% chance of drought) and decision 10 (100% chance of drought), is significantly higher for those shown the ambiguity treatment at the 5 and 10% levels respectively, compared to those presented with the risk treatment (H0: mean of land allocated by farmers presented with ambiguity is higher than those presented with the risk treatment). T-tests for male and female farmers on average land allocation shows no significant differences for all decisions except for decision 5 where tests show that the average proportion for males is higher than that for females at the 10% level of significance for the ambiguity treatment (p=0.07). Results are shown in Table 2.12.

Results of the DH model on factors affecting adoption decisions and intensity of adoption are presented in Table 2.13. Significant factors on whether or not a farmer will adopt the new DT variety at the 10% (5-15%) level of drought are: membership of an association, district, DT awareness and radio/TV ownership.

Table 2.13: Double hurdle model results

	Adoption[a]	**Intensity of adoption**[b]
female	0.410	12.97
	(0.281)	(10.62)
age	-0.009	-0.17
	(0.009)	(0.33)
married	0.423	6.35
	(0.313)	(11.93)
education	-0.228	-11.46
	(0.277)	(10.28)
family size	0.120	-1.33
	(0.086)	(2.56)
children	-0.162	0.22
	(0.122)	(3.86)
total land	0.043	**-5.68***
	(0.066)	(2.94)
maize area	-0.166	-7.86
	(0.137)	(5.30)
extension	0.212	**-40.18****
	(0.426)	(20.16)
association	**0.801*****	19.96
	(0.262)	(12.45)
district	**1.175*****	**21.55****
	(0.281)	(10.76)
treatment	-0.075	-6.96
	(0.240)	(8.65)
DT aware	**-0.797****	-10.43
	(0.323)	(11.65)
radio/TV	**-0.669***	-3.98
	(0.380)	(10.78)
mobile phone	-0.011	30.92
	(0.468)	(19.07)
constant	0.234	54.09*
	(0.879)	(32.14)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
[a] probit model of DH model(Tier 1), [b] truncated model of DH model (Tier 2)

Farmers who are members of an association and from dry districts (Insiza and

Shurugwi) are more likely to adopt the new DT variety at the 1% level. Associations are sources of information where farmers gain knowledge about new technologies and hence they would be more likely to adopt. Farmers who indicated they were aware of other DT varieties were less likely to adopt at the 10% level because they probably have already allocated land to the varieties they already know. It could also be because they don't trust DT varieties. In the field survey, farmers were asked to name the DT varieties that they knew if they indicated they were aware of any; however it was noted that some of the varieties that farmers were indicating to be DT, were in fact NOT drought tolerant. If these farmers adopted these varieties and they lost their produce in the event of a drought, they will be less likely to adopt the new DT variety.

Ownership of a radio/TV has negative impact on adoption. This is an unexpected result as radios/TVs are sources of information and also an indicator of wealth. Owners might be less likely to adopt if they do not receive any information on agriculture, new technologies and so forth or if the information they get from these sources does not encourage the adoption of DT varieties. If used as an indicator of wealth, then the wealthy are less likely to adopt at the 10% level of drought because they probably already have enough income to diversify into other ventures and are reluctant to adopt at such a low probability of drought.

Factors that influence the intensity of adoption are different from the adoption ones except for 'district'. Total land and extension now become negatively significant. Similar results were found by Legese et al. (2009). As the farm size increases, farmers were proposing to allocate less land to the new DT variety. Total land was also used as a proxy for wealth. For those farmers with less land, a new DT variety might be a way to move them out of poverty hence they are more likely to put more land under the new crop. Bigger farm owners, on the other hand, can afford to diversify to other crops or alternative projects hence they might allocate less land to the new DT crop. Depending on what the new technology might offer, farm owners with smaller farms might put more land under the new technology in order to meet their subsistence needs. We expected farmers who indicated they had contact with extension agents to put more land under the new crop but that is not the case. Extension agents are the first point of contact for smallholder farmers in Zimbabwe, and offer various services such as; agricultural information, support and training. The extension agents can be governmental or nongovernmental. Result might indicate that the farmers are not necessarily getting information about DT varieties from extension officers.

2.6. Summary and discussion of results

The majority of the farmers exhibit extreme risk and ambiguity aversion (73.2% and 78.6% respectively) and about 65% choose to adopt at all levels. Previous studies also show higher degrees of risk aversion by smallholder farmers. A study in Zambia, found that more than 80% of the farmers exhibited moderate to extreme risk aversion (Wik et al. 2004). Around 56% of the participants in Yesuf and Bluffstone (2007) study in Ethiopia exhibited severe to extreme risk aversion at the highest level of a Binswanger (1980) type game. Ajijola et al (2011) found 97.5% of the farmers in Nigeria, risk averse – however this was not an experimental study. Brüntrup (2000), found 35-45% percent of Benin farmers in the severe to extreme risk aversion category. About 73.3% of the males were extremely risk/ambiguity averse compared to 77.8% of the female farmers. This supports previous results indicating that women are more averse compared to men.

Table 2.14 gives a summary of the significant variables in the regression models and whether or not the relationship with the dependent variable was positive (+) or negative (-).There are variations in factors affecting risk/ambiguity aversion when data is disaggregated by district, sex of respondent and marital status.

a) Whether or not participants were presented with the risk or ambiguity treatment did not have a significant impact on attitudes for almost all categories but there are significant differences for the male participants (male participants who were shown the ambiguity treatment chose more safe choices compared to those shown the risk treatment). Farmers in Insiza district presented with the risk treatment were more averse.
b) Membership of an association is mostly a positive significant determinant for adoption, adopting at all levels and risk/ ambiguity aversion attitudes of farmers. Farmers who are members of an organisation are likely to meet and discuss with others different farming methods.

Table 2.14: Summary of regression results disaggregated by different groups*

Model	Probit	Ordered probit	Interval regression	Double hurdle	Double hurdle
dependent / category	Adopt all	Number of safe choices	CRRA interval	Adoption	Intensity of adoption
All	Total land (+) Association(+) District (+) Maize area(-) Married (+) Radio/TV(-)	Total land (+) Association(+) District (+) Radio/TV(-)	Total land (+) Association(+) District (+) Radio/TV(-)	Association(+) District(+) DT aware(-) Radio (-)	Total land (-) Extension(-) District (+)
Risk	Married (+) Total land (+) District (+) Mobile (+) Radio/TV(-)	Total land (+) Radio (-) Mobile (+)	Total land (+) Radio (-) Mobile (+)	-	-
Ambiguity	Association(+) District (+) DT aware (-) Mobile (-)	Association(+) District (+) DT aware (-)	Association(+) District (+) DT aware (-)	-	-
Male	District (+) Age (+) Total land (+)	Treatment(-) Mobile(+)	-	-	-
Female	Association(+) DT aware (-) Radio/TV(-)	Association(+) District (+) DT aware (-)	Association(+) District (+) DT aware (-)	-	-
Married	District (+) Total land(+) Age (+)	District(+) Mobile(+)	Mobile(+)	-	-
Single parent	Association (+) Age(-) Radio/TV(-) Total land(+) Education(-)	Education(-)	Education(-)	-	-
Wet	DT aware(-)	Mobile (+)	Female(+) Family size (+) Mobile(+)	-	-
Dry	Association(+)	Association (+)	-	-	-
Bindura		Married(-) Education(-) Family size(+) Children(-) Extension(-) Radio/TV (-) Mobile(+)	Married(-) Family size(+) Children(-) Radio/TV (-) Mobile(+)	-	-
Insiza	Children (+) Association (+)	Children (-) Association(+) Treatment (+)	Children (-) Association(+) Treatment (+)	-	-
Shurugwi	Association (+) Family size (-) Children(+)	Association (+)	Association (+)	-	-
Zvimba	Female (+) Married(+) Age(+) Maize area (-) Association (+)	Female (+) Married (+) Total land (+) Mobile(+)	Female (+) Married (+) Total land (+) Mobile(+)	-	-

*relationship with dependent variable in parenthesis

In groups, smallholder farmers can learn from each other, exchange ideas and perhaps encourage each other to try new technologies; hence members might adopt in order to learn the new technology. For male participants, membership to an association is not a significant determinant for adopting at all levels, and risk aversion/ ambiguity aversion whereas it is significant for the female farmers and single parents (mostly divorced women). This maybe because perhaps associations are exclusively male or female and in the later, women might discuss more about farming and feeding the family compared to their male counterparts. There are gender differences for farmers in Zvimba with females more risk averse but no differences for participants in other districts or categories. This maybe because in Zvimba there are more gender disparities compared to other districts.

c) Overall, as expected and taking into account the nature of the experiment, farmers in dry districts are more ambiguity/risk averse and are more likely to adopt at all levels. District is however not a significant factor for farmers presented with the risk treatment and single parents. This might indicate that single parents have the same preferences despite their geographical location.

d) Total land and radio/TV ownership which can be used as proxies for wealth, have a significant impact on adoption at all levels and risk aversion for most of the categories but not for participants presented with the ambiguity treatment. Total land has a positive relationship, whilst radio/TV ownership has a negative one. The more land a household has, the more likely the respondent is to be risk/ambiguity averse or adopt at all levels. This maybe because with more land at their disposal, farmers can diversify and try out new crops. The variable is significant for male farmers but not for females possibly because the former 'own' the land in the household. Total land, however has a significant negative relationship with intensity of adoption: as the farm size increases, farmers are proposing to allocate less land to the new DT variety. For farmers with less land, a new DT variety might be a way to move them out of poverty; hence they are more likely to put more land under the new crop unlike bigger farm owners who can afford to diversify to other crops or projects who might allocate less land to the new DT crop. Farmers who indicated radio/TV ownership were less likely to adopt at all levels and were less risk averse.

e) Mobile phone ownership increases risk aversion in almost all categories. In terms of adoption at all levels, it has positive relationship for those presented with the risk treatment and for those presented with ambiguity treatment the relationship is negative. Access to a mobile phone has benefits for smallholder farmers which include better access to extension officers, markets, finance and information. Mobile phones help maintain and strengthen social networks which are essential knowledge sharing platforms in smallholder agriculture.

f) Farmers who indicated that they were aware of other DT varieties are less likely to be ambiguity averse and less likely to adopt or adopt at all levels. Since they are already aware of other varieties, they may already be using them hence they might not be so keen on adopting. It could also be because these farmers do not trust DT varieties. In the field survey, farmers were asked to name DT varieties they were aware; however it was noted that some of the varieties that farmers were indicating to be DT, were in fact NOT drought tolerant. If these farmers adopted these varieties and they lost their produce in the event of a drought, they will be less likely to adopt the new DT variety

g) The age of respondent is significant for some of the categories. Older male farmers, older married farmers and older farmers from Zvimba are more likely to adopt at all levels, whilst the older single parents are less likely to do so. Studies that find older farmers more risk averse include Moscardi and de Janvry (1977) and Nielsen et al (2013) . Married farmers were more risk averse in Zvimba but less so in Bindura. When all farmers are aggregated, the married are more likely to adopt at all levels and so are the married individuals presented with the risk treatment.

h) Education has a negative relationship with ambiguity/risk aversion for the single farmers and for Bindura farmers. Participants with higher education were less risk averse than those with lower levels of education. These results are consistent with Nielsen et al. (2013). Educated farmers are more likely to adopt new technologies and in our experiment, farmers had to choose whether or not to adopt a new DT variety.

i) For the individual districts, other factors that are not significant in the earlier analysis become significant. These are; number of children (Bindura, Insiza and Shurugwi), family size (Shurugwi and Bindura) and access to extension agents (Bindura). Respondents in households with more children were more likely to adopt at all levels but less risk/ambiguity averse. For Bindura the bigger the family size, the more risk averse the respondent. In Shurugwi, households with larger family sizes are less likely to adopt at all levels. A larger family size may mean more labour if most of the household members are past the age where they can provide labour or it can mean more mouths to feed if there are more children who cannot provide labour hence results can be mixed when it comes to technology adoption.

The behaviour of farmers in our sample can be explained by the safety first models of choice under uncertainty, also known as the disaster avoidance approach.[24] Lipton (1968) argues that the risk aversion behaviour of smallholder farmers is based on securing household needs and avoiding starvation. Farmers in our sample could be avoiding starvation in the case of a drought by adopting even at the smallest probability of a drought occurring. When individuals are asked to make a decision where they have to choose between alternatives, they may make their decision in such a way as to minimise falling below a certain threshold level (subsistence minimum). In our case, the subsistence minimum is the yield per hectare required to avoid starvation in case a drought occurs. According to (Roy 1952) "...*the principle of Safety First asserts that it is reasonable, and probable in practice, that an individual will seek to reduce as far as is possible the chance of a catastrophe occurring*." In our experiment, farmers risked losing all their produce in the event of a drought (disaster) if they chose not to. The reason to adopt at all levels for most of the farmers could be because even if they could have maximised their yield by risking non adoption (yield of 10t/ha), the risk averse farmers preferred the drought tolerant variety which offered a lower average yield but guaranteed food security in case of a drought (even at the smallest probability). In this instance, the payoff was either equal to or greater than their threshold.

Farmers' behaviour could also have been influenced by their farming experiences (in terms of drought/ past harvests) coupled with the economic downturn over the past few years in Zimbabwe. Most farmers indicated that the 2007/2008 season was the worst they have ever experienced in their lives. This was attributed to lack of agricultural inputs (e.g., seed, fertilizer), record hyperinflation, drought and political violence during elections which were held at that time. This season was possibly a reference point for farmers on which they based their decisions.

It could also be possible that the risk/ambiguity averse behaviour was related to the farmers' desire to 'learn' and try out new technologies especially drought tolerant varieties given the recurrent droughts. The majority of farmers indicated that if a

[24] This is also related to the precautionary principle which is used mostly in public policy particularly in sustainable development. Reference of the concept is found in the 1992 Rio Declaration on Environment and Development: Principle 14 states that, "In order to protect the environment, the precautionary approach shall be widely applied by States according to their capabilities. Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation".http://www.unep.org/Documents.Multilingual/Default.asp?DocumentID=78&ArticleID=1163
This is a case of prevention is better than cure; you don't have to wait for a disaster to happen before you act.

new variety was distributed, they would adopt as they are always willing to ‘learn’ but they would ‘test’ it on a portion of their land thus giving them a chance to compare with the varieties they are familiar with. As part of the experiment, participants had to indicate how much of their land they would allocate to the drought tolerant variety. Results show that the proposed proportion of land at all the analysed decisions for farmers presented with the ambiguity treatment, was higher than for those shown the risk treatment. Regression results show that the adoption of a new DT variety and intensity of adoption is influenced by different factors.

When asked how and why they made their decisions, some of the responses from the farmers were:

- *‘...goal is food security so will adopt even at the smallest probability of drought.’*
- *most indicated they would not grow new crop on the whole land area but indicated they would increase the area allocated in the next season if they planted it this season and it did well*
- *‘...would like to test new crop...’*
- *‘...will try new crop since it’s new and we want to learn...’*
- *‘...recurrent droughts so if crop is drought tolerant will adopt to ensure families are food secure...’*
- *‘...will produce something with the new crop even if there is a drought....’*
- *‘...will not adopt because I trust my old varieties that I have been using for a long time...’*
- *One farmer indicated that at 75-85% of drought, they would switch to a new crop completely*

It is also possible that some of the farmers anticipated food handouts so perhaps that influenced their decision making. Over the past few years, due to the economic downturn in Zimbabwe, coupled with poor rainy seasons, lack of inputs among other factors, has seen smallholder farmers producing very little and a subsequent influx of Non-Governmental Organisations (NGOs) flooding the rural market with food aid.

Participants might also have overweighed the probabilities i.e. when participants were told a low probability of drought occurring, they behaved as if the chance of the event happening was higher than what the experimenter would have told them, hence they will adopt even at the lowest probability. This can be attributed to past experiences of recurring droughts. As shown in Table 2.4(b), more than half of the participants indicated that they were experiencing either increased incidences of droughts or mid season dry spells. Most smallholder farmers in Zimbabwe sell their produce to the government run Grain Marketing Board. However, over the past years the government has not been making timely payments to farmers thus increasing their risk. Adoption at all levels could be a cushion for the farmers in drought years since they know they will definitely produce.

Participants made their decisions after being told the probability of a drought occurring. Depending on whether or not participants get accurate weather information regarding seasonal weather forecasts, their decision making might be biased. If say in the past, the weather predictions differed from what farmers experience in the actual season for example if a normal season is predicted but instead farmers experience a drought or a mid season dry spell, then even if next season the predictions say there is no drought or the probability of a drought occurring is low, farmers might suppose otherwise. In the questionnaire farmers were asked about their source of weather information and whether or not they were satisfied with the information and if it was accurate. Around 44% indicated that the weather information they receive is somewhat accurate, 21% indicated that there was very little accurate information whilst 10% indicated that the information they received was not accurate at all. Close to half (47%) of those who indicated that the information they received was somewhat accurate choose to adopt at all decision levels whilst around 17% of those who adopted at all levels indicated that the weather forecast information was rarely accurate.

2.7. Conclusion

The study ascertained the risk and ambiguity attitudes of Zimbabwean smallholder farmers and factors affecting these attitudes using experimental and field data. The study ascertained the risk and ambiguity attitudes of Zimbabwean smallholder farmers and factors affecting these attitudes using experimental and field data. The purpose of the experiment was to determine at what risk levels farmers would be willing to adopt a drought tolerant variety and factors affecting this decision- and to assess if there were differences under risk and ambiguity from a gender perspective. Furthermore, we analyse the proportion of land participants are willing to allocate to the new DT variety. Ideally we would hope for farmers to be neutral but as our experiment results show, individual risk and ambiguity attitudes depend on different characteristics, context, decision that the farmer has to take and so forth. In our experiment, adoption was the safe lottery whilst non adoption was the risky option. Our results are consistent with most studies and show that smallholder farmers are generally averse; in our case however farmers are extremely averse. Most of the farmers exhibit extreme ambiguity and risk aversion in an experiment on technology adoption given different probability levels of a drought occurring. Further research can be undertaken with a control treatment where non adoption in the safe option in order to test for framing effects. As discussed earlier, most empirical work that has been carried out show, that smallholder farmers are risk averse (Binswanger, 1980; Teklewold and Köhlin, 2011; Yesuf and Bluffstone, 2009). Results from the study can be used by seed companies who produce new varieties. Seed companies like SIRDC, Seed Co and the International Maize and Wheat Improvement Centre (CIMMYT) are constantly testing and disseminating new varieties. The latter is currently involved in the Drought Tolerant Maize for Africa (DTMA) initiative[25] which seeks to provide insurance against risks by developing and disseminating drought tolerant varieties that produce yields in both good and reduced rainfall seasons. Insurance companies offering weather based insurance can use the results on the risk attitudes to construct insurance models for the different groups of farmers.

This study found that women were more risk/ ambiguity averse compared to their male counterparts. The risk and ambiguity aversion attitudes of farmers in our sample can be expained by the safety first/disaster avoidance principle. Most farmers (about 65%) adopt at all levels of drought occurring. DT varieties are examples of technologies that reduce exposure to risk and ambiguity. Hence, farmers will most likely adopt such technologies even at very low probabilities of a drought occurring in order to avoid starvation. Investing in DT varieties is a form of insurance against weather or climate change risk.

[25] http://dtma.cimmyt.org/index.php

Associations or farmer groups should be strengthened and supported to encourage more dissemination of agricultural information. Through associations, there is potential for smallholder farmers to learn from each other and network. Membership of an association is positively significant for female farmers at all analysis levels showing that perhaps it's more of the women that attend association meetings or it could be that when women meet they discuss more issues to do with farming compared to their male counterparts. Overall, there are no significant differences in gender when the aggregated data is analysed. However, gender differences were found for farmers in the wet areas and Zvimba as an individual district. There are differences in the factors that affect the ambiguity and risk preferences of male and female farmers when they are analysed separately. Total land is a significant factor in adopting at all levels for the men but that is not the case for women. Men are the owners of land and have more access compared to women. There is a need to continue government and private sector initiatives and legislation to ensure women empowerment and more access to productive assets.

The desire to try out new technologies based on past experiences (persistent droughts, economic crisis and political uncertainty) could be what was pushing farmers to be extremely risk/ambiguity averse and be willing to adopt the new DT variety. Further work including variables on past experiences and political and economic uncertainty might shed more light on their interaction with technology adoption. Changing the framing and instead using 'probability of rain' might provide different results. Our experiment was in the 'gain domain' but further work can be done to measure preferences in the 'loss domain'.

Ownership of and access to mobile phones was seen to have a positive significant impact on farmers' adoption decisions. There is a need therefore for more to be done to ensure that mobile phones are used as information and knowledge platforms for the rural population. There has been a rapid increase in mobile phone usage and access in developing countries over the past decade, but more effort is needed to ensure mobile phones promote agricultural development by being a tool for: information dissemination (e.g. on prices, weather, new technologies and so forth), learning and strengthening social networks. Mobile phones are normally just used to keep in touch with friends and family members. Studies undertaken on impact such as mobile phones on developing countries indicate positive results for instance, raised incomes, reduced risks in Tanzania (Furuholt and Matotay 2011) and reduction in price dispersion across grain markets in Niger (Aker 2010).

Contact with extension agents is not a significant determinant in the analyses we performed except the negative relationship on intensity of adoption. Extension agents are the first point of contact for smallholder farmers in Zimbabwe, and offer various services such as agricultural information, support and training. There is need for more support and emphasis on the importance of extension services to farmers especially related to drought tolerant varieties by the government.

Results indicate the need to disaggregate samples when analysing research results as there maybe underlying factors affecting different groups. Farmers are heterogeneous and our study reveals differences in factors affecting risk/ambiguity aversion when the sample was analysed by sex of respondent, marital status and geographical location (district) which are not reflected in the aggregate data. This will ensure that development planners and policy makers tackle and target the different priorities each sub group might require. The results thus provide a baseline and we do acknowledge that there are certainly parts of the design that require further research and comparisons to understand the underlying factors driving our results.

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Appendix 2.1: Experiment Instructions

You are about to participate in an economic experiment on crop decision making. The experiment consists of 10 decisions in each part. At the end of the experiment, one round will be randomly selected for payment. Your total earnings which will be paid using maize and cowpea seed packs maize will be the cash equivalent of the selected outcome. Payoffs are in tonnes/ha where 1 tonne/ha= $1. Earnings depend on your **individual decisions**. Through your decisions, you might earn a considerable amount of money.

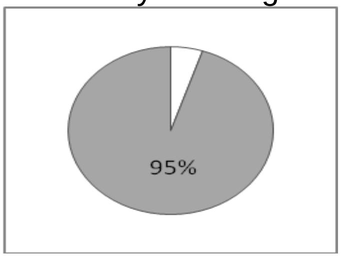
Do not communicate with the other participants. If you have any questions at any time, please raise your hand and someone will come and assist you.

The experiment involves making a series of choices from two options. You are to choose whether or not to adopt a new drought tolerant maize crop variety. You are told the exact probability that there will be a drought (e.g. 40% probability of drought) OR you are told a range of the probability that a drought will occur (e.g. 20-60% probability of drought). The new crop variety can do well in both rainy and drought conditions.

To help you decide you are given a payoff table, a chart showing the probability that a drought will occur and asked to choose which option you prefer. The payoff table shows that if you adopt the new drought tolerant crop variety and there is a drought, your payoff will be **4** whilst if you do not adopt and there is a drought, your payoff will be **0** (lose everything). Likewise, if you decide to adopt and there is a good rainy season, your payoff will be **6** and if you do not adopt and it rains, your payoff will be **10**.

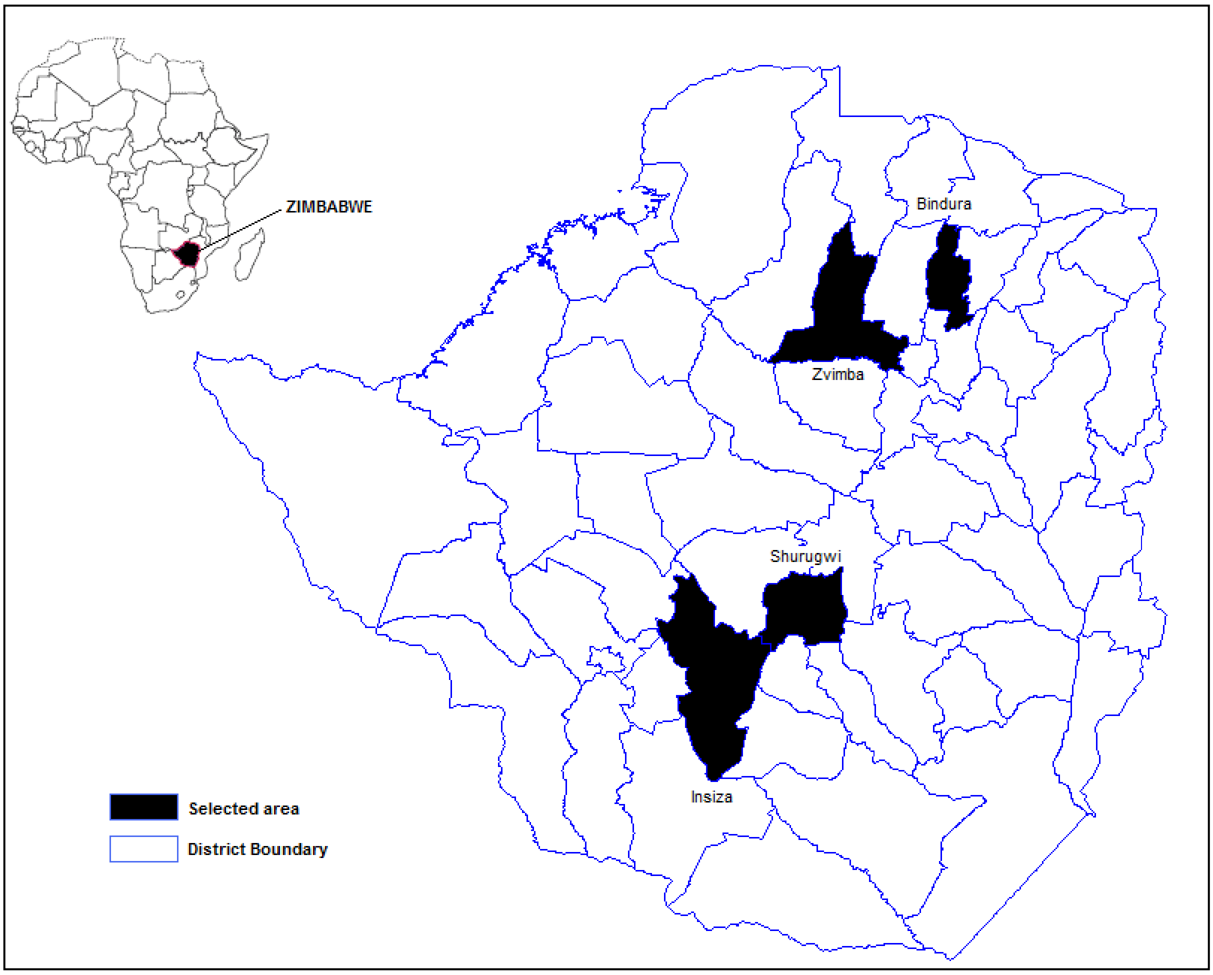
Decision 1 (Please tick your choice)		Drought	Rain
	Adopt	4	6
	Do not adopt	0	10

Probability of drought



Let's look at Decision 1 for instance, you are told that there is a 95% chance of a drought occurring (which means that there is a 5% chance of a good rainy season); given the payoffs above you have to choose which option you prefer (that is **adopt** the new drought-tolerant variety or **do not adopt** the new drought-tolerant variety).

Appendix 2.2: Study areas



Appendix 2.3: Summary statistics by district and gender

a) Age by gender of respondent (married vs. single parents)

	n	mean (s.d) male	n	mean (s.d) female
Married(all)	87	54.3 (15.7)	54	46.8 (11.3)
Bindura	20	48.1 (16.0)	17	38.2 (6.2)
Insiza	18	56.7 (14.2)	13	49.4 (14.9)
Shurugwi	27	55.0 (18.5)	9	50.2 (7.8)
Zvimba	22	57.2 (11.7)	15	52.4 (8.8)
Single (all)	7	49.7(19.3)	37	55.8 (13.7)
Bindura	3	45.0(23.4)	7	44.6 (8.7)
Insiza	0	-	7	67.1 (11.2)
Shurugwi	1	26.0	12	56.3 (12.4)
Zvimba	3	62.3(3.2)	11	55.2 (14.2)

b) Summary statistics by district

		Bindura n=50	Insiza n=39	Shurugwi n=50	Zvimba n=51
		%	%	%	%
Education	None	-	2.6	2.0	1.9
	Primary	12.0	61.6	38.0	62.8
	Secondary	88.0	35.9	60.0	23.5
	Tertiary	-			11.8
Marital status	Married	80.0	79.5	74.0	72.6
	Widowed	16.0	20.5	16.0	23.5
	Divorced	4.0	-	6.0	3.9
	Single	-	-	4.0	-
Main source of income (top 3)	crop sales	74.0	-	34.0	68.6
	casual labour	-	15.4	16.0	-
	gold panning/mining	-	33.3	-	-
	remittances	12.0	-	16.0	13.7
	artisan/petty trade	10.0	15.4	-	-
	vegetable sales	-	-	-	5.9
Contact with extension agent (yes)		84.0	97.4	98.0	62.8
Member of association (yes)		52.0	53.9	86.0	64.7
Aware of DT varieties (yes)		62.0	97.4	78.0	76.0
Access to mobile phone (yes)		89.3	94.7	91.8	90.0
Own radio/ TV		90.0	81.6	75.5	88.2

c) Summary statistics by district and gender of respondent

		Bindura		Insiza		Shurugwi		Zvimba	
		M	F	M	F	M	F	M	F
	N	25	25	18	21	28	22	25	26
Education	None	-	-	-	4.0	3.6	-	-	3.9
	Primary	4.0	20.0	55.6	66.7	25.0	54.6	56.0	69.2
	Secondary	96.0	80.0	44.4	28.6	71.4	45.5	28.0	19.3
	Tertiary	-	-	-	-	-	-	16.0	7.7
Marital status	Married	88.0	72.0	100	61.9	96.4	45.5	88.0	57.7
	Widowed	4.0	28.0	-	38.1	0	36.4	12.0	34.6
	Divorced	8.0	-	-	-	3.6	13.6	-	7.7
	Single	-	-	-	-	-	4.6	-	-
Contact with extension agent (yes)		80.0	88.0	94.4	100	96.4	100	56.0	69.2
Member of association (yes)		40.0	64.0	50.0	57.1	75.0	100	56.0	73.1
Aware of DT varieties (yes)		28.0	96.0	94.0	100	75.0	81.8	72.0	80.0
Access to mobile phone (yes)		84.0	95.5	88.2	100	100	81.0	91.7	88.5
Own radio/ TV		96.0	84.0	88.2	76.2	81.5	68.2	92.0	84.6

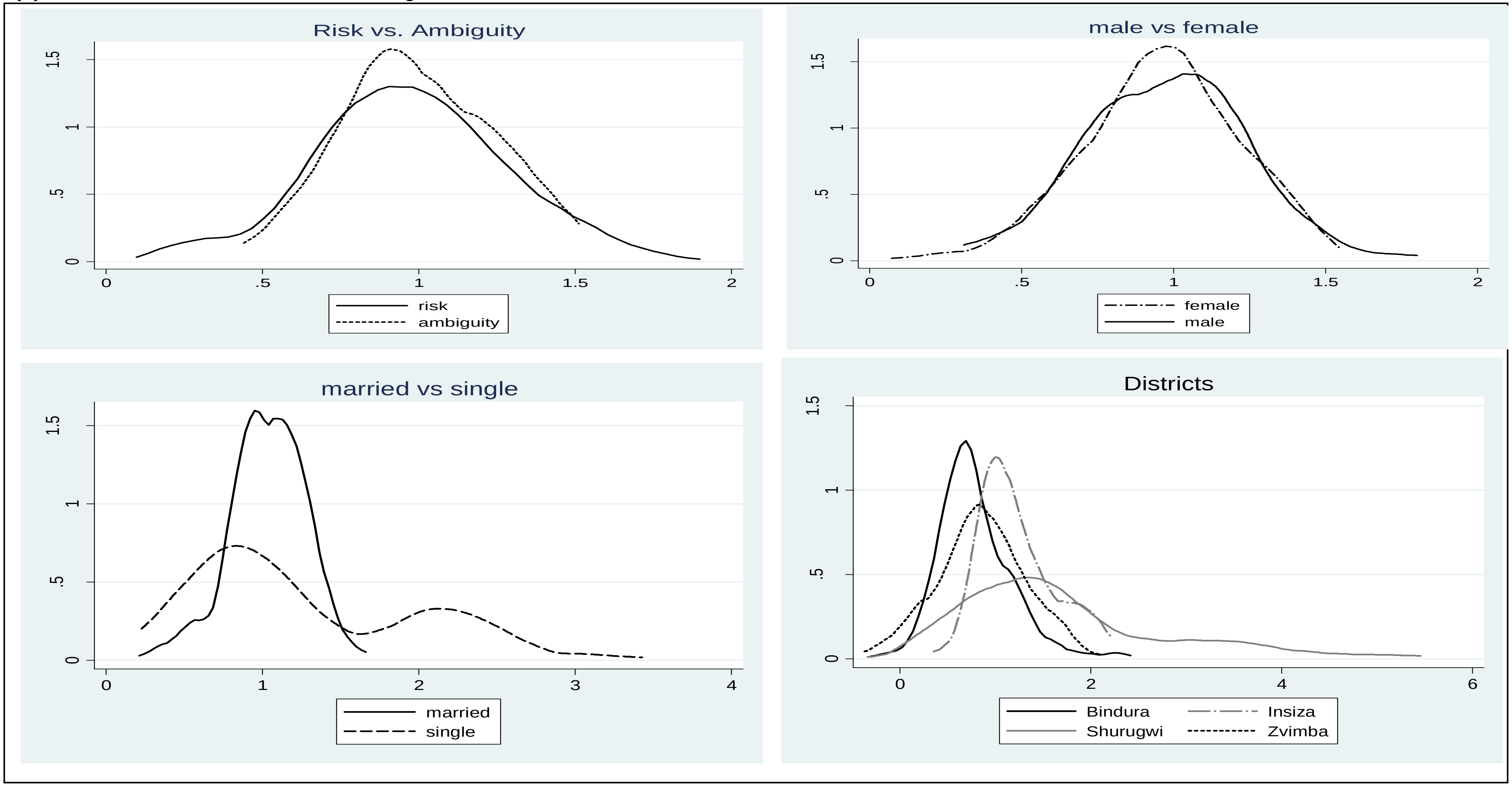
Appendix 2.4: Interval regression results on ambiguity/risk preferences

(a): Interval regression models of ambiguity/risk preferences (dependent variable-CRRA range)

	all	**risk**	**ambiguity**	**female**	**male**	**married**	**single**	**wet[a]**	**Bindura**	**Insiza**	**Shurugwi**	**Zvimba**
female	0.130	0.218	0.141			0.127	0.137	0.171*	0.166	-0.109	-0.121	0.550**
	(0.090)	(0.142)	(0.119)			(0.108)	(0.198)	(0.098)	(0.164)	(0.116)	(0.422)	(0.254)
age	-0.002	-0.001	-0.004	-0.006	0.003	0.002	-0.003	0.000	-0.006	-0.001	0.004	0.010
	(0.003)	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.016)	(0.008)
married	0.143	0.233	0.095	0.103	0.033			0.077	**-0.284***	0.118	-0.231	**0.573****
	(0.103)	(0.168)	(0.119)	(0.092)	(0.226)			(0.107)	(0.153)	(0.107)	(0.538)	(0.259)
education	0.026	-0.028	0.034	0.052	-0.076	0.051	**-0.307****	0.133	-0.114	-0.061	-0.093	0.197
	(0.087)	(0.137)	(0.111)	(0.090)	(0.146)	(0.106)	(0.150)	(0.090)	(0.154)	(0.097)	(0.517)	(0.194)
family size	0.015	-0.0028	0.028	0.012	0.057	0.037	-0.027	**0.086***	**0.189****	0.012	-0.059	-0.035
	(0.029)	(0.037)	(0.039)	(0.035)	(0.050)	(0.037)	(0.055)	(0.046)	(0.077)	(0.031)	(0.100)	(0.083)
children	-0.007	0.004	-0.034	-0.039	-0.026	-0.036	0.076	-0.072	**-0.171****	**-0.108****	0.165	0.106
	(0.039)	(0.057)	(0.053)	(0.047)	(0.064)	(0.048)	(0.084)	(0.050)	(0.079)	(0.047)	(0.183)	(0.093)
total land	**0.036***	**0.085****	0.007	0.003	0.044	0.029	0.006	0.0272	-0.010	-0.002	-0.102	**0.089***
	(0.021)	(0.041)	(0.025)	(0.027)	(0.031)	(0.024)	(0.053)	(0.022)	(0.035)	(0.039)	(0.118)	(0.051)
maize area	-0.057	-0.059	-0.075	0.022	-0.100	-0.042	0.023	-0.057	0.029	0.016	0.243	-0.172
	(0.047)	(0.072)	(0.070)	(0.050)	(0.105)	(0.057)	(0.080)	(0.079)	(0.108)	(0.045)	(0.294)	(0.205)
extension	-0.109	-0.089	-0.197	0.179	-0.104	-0.183	0.169	-0.082	-0.140		-0.485	-0.023
	(0.120)	(0.179)	(0.159)	(0.167)	(0.184)	(0.154)	(0.172)	(0.106)	(0.147)		(775.2)	(0.201)
association	**0.279*****	0.167	**0.310*****	**0.316*****	0.125	0.154	0.262	0.049	0.067	**0.277*****	**0.800****	**0.433***
	(0.085)	(0.128)	(0.108)	(0.090)	(0.137)	(0.102)	(0.163)	(0.097)	(0.112)	(0.093)	(0.395)	(0.229)
district	**0.259*****	0.125	**0.367*****	0.142	0.233	0.184	0.160					
	(0.095)	(0.131)	(0.136)	(0.112)	(0.154)	(0.112)	(0.173)					
treatment	-0.083			-0.041	-0.197	-0.084	0.104	-0.035	-0.100	**0.175****	-0.400	0.060
	(0.078)			(0.082)	(0.128)	(0.094)	(0.120)	(0.088)	(0.109)	(0.072)	(0.382)	(0.160)
DT aware	-0.103	0.114	**-0.292****	**-0.370****	0.059	0.075	-1.465	-0.146	-0.148	-0.767	-0.200	-0.206
	(0.098)	(0.141)	(0.131)	(0.187)	(0.145)	(0.118)	(122.0)	(0.100)	(0.151)	(95.13)	(0.405)	(0.199)
radio/TV	**-0.242***	**-0.378***	-0.111	**-0.276***	-0.048	-0.207	-0.268	-0.218	**-0.405****	0.079	-2.315	0.261
	(0.130)	(0.202)	(0.184)	(0.146)	(0.207)	(0.161)	(0.281)	(0.162)	(0.198)	(0.136)	(209.5)	(0.389)
mobile	0.144	**0.478****	-0.140	-0.094	0.339	**0.375****	-1.359	**0.317****	**0.364****	-0.305	-1.599	0.187
	(0.134)	(0.203)	(0.207)	(0.189)	(0.212)	(0.162)	(165.6)	(0.136)	(0.172)	(67.75)	(332.2)	(0.231)
constant	0.793***	0.235	1.294***	1.373***	0.195	0.467	3.529	0.398	0.957***	2.095	5.389	-1.234
	(0.274)	(0.465)	(0.373)	(0.317)	(0.479)	(0.337)	(205.6)	(0.309)	(0.370)	(116.8)	(816.9)	(0.919)
ln (σ)	-0.961***	-0.984***	-1.124***	-1.402***	-0.836***	-0.945***	-1.539***	-1.168***	-1.506***	-2.229***	-0.714**	-1.074***
	(0.112)	(0.156)	(0.161)	(0.168)	(0.151)	(0.132)	(0.210)	(0.132)	(0.165)	(0.313)	(0.316)	(0.212)
Predicted CRRA	0.993	0.973	0.998	0.959	0.974	1.033	1.279	0.871	0.789	1.226	1.721	0.855
Standard deviation	0.231	0.305	0.241	0.251	0.269	0.238	0.717	0.225	0.385	0.398	1.120	0.469

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, [a]the dry districts did not converge

(b): Predicted CRRA from the interval regression



The graphs, reiterate that those shown the ambiguity treatment and female farmers are slightly more risk averse. The double peaks on the single parents could be because of the two main groups in the single parent category (male headed and female headed household heads)- with the male headed (1st peak) less risk averse compared to the female headed ones (2nd peak). The dry districts (Shurugwi and Insiza) as expected are more averse compared to the wet districts.

CHAPTER 3: Risk and ambiguity attitudes of vocational college students in Zimbabwe

3.1. Introduction

In our day to day lives, we face many decisions that have uncertain outcomes, uncertain probability of occurrence (which may or may not be quantified) and/or imprecise information. How individuals make their decisions and process information when making choices under uncertainty potentially has significant impacts on policy, can inform how uncertainty information should be communicated and can help behavioural scientists gain insights into preferences and certain behaviour between different groups of individuals. It therefore becomes fundamental to understand the behavioural attitudes of individuals when faced with risky and ambiguous situations as these determine choice under uncertainty.

Research, pioneered by Ellsberg (1961) demonstrated that decision makers (DM from here on) prefer to bet on risky lotteries with known probability compared to ambiguous lotteries with unknown probability. This is known as *ambiguity aversion. Risk aversion* occurs when an individual prefers a certain option compared to an uncertain one even though the later might have higher expected payoffs, thus minimising their potential losses. Decision making when information is presented as risk, is potentially different from decision making under ambiguity. Take for instance a simple decision such as whether or not to carry an umbrella which may depend on the chance of rain information provided by the meteorological department or a decision whether or not to go ahead with a new type of medical treatment. An individual presented with a probability forecast of '10% chance of rain' might not necessarily make the same decision as another DM who is given the 'chance of rain' as 0-20%, though the two have the same subjective probability[26]. The former has an objectively known probability whilst the later has an imprecise probability of the event happening. Will these individuals behave in the same way? Will the later DM use the minimum probability (0%), maximum probability (20%), centre (10%) or anywhere within the range when making their

[26] Assume there is an equal likelihood of each probability occurring; hence evaluate using the middle of the range. According to the Subjective Expected Utility model, the behaviour of an individual when presented with the range (0-10%) or point estimate (5%) would be the same.

decision? These are some of the questions that this study will try and answer.
In this chapter we focus on assessing the risk and ambiguity attitudes of vocational college students using experimental economics. A between-subject approach in conjunction with a modified Holt and Laury (2002b) multiple price list (MPL) is used to assess attitudes. One group of participants was presented with exact probabilities of a drought occurring (for example 10% chance of drought) whilst the other group was shown ambiguous probability ranges (for example 5-10%) and had to decide whether or not to adopt a drought tolerant crop variety.

Experiments were conducted with students from vocational agricultural colleges in Zimbabwe. In typical economic experiments, undergraduate students at universities are used as subjects. However, in this study we used subjects at vocational colleges that specialise in agricultural courses and have never been exposed to experimental economics, but who will in the near future be making farming decisions under uncertainty and offering advice to farmers. Most of the studies undertaken with using university students find them generally risk averse. Harrison and Rutström (2008) review studies measuring risk preferences using experimental economics in the laboratory and conclude that there is convincing evidence of risk averse behaviour among participants with few exhibiting risk taking or risk neutral behaviour. Our study elicits the risk and ambiguity attitudes of students with the hypothesis that students would be risk averse and ambiguity averse on average (based on past studies that have been conducted with students in university settings). Ideally we would expect participants to be risk neutral and act 'rationally' but risk and ambiguity attitudes measure individual behaviour. Depending on the context of the decision, past experiences and so forth participants are bound to have different attitudes. Hence we are interested in ascertaining and characterising the determinants of risk and ambiguity attitudes of vocational students in our sample.

Section 3.2 gives a summary of some of the studies done in a laboratory setting with university students, mostly in developed countries on various subjects. Very few studies were found which focused on risk and ambiguity preferences and used African university students as subjects (for risk see., Lammers and Van Wijnbergen 2008, Tanner, Lusk and Tyner 2005, Vieider, Chmura and Martinsson 2012). Studies on ambiguity aversion are almost nonexistent. Comparisons between the behaviour of students from developed countries, developing countries (Africa in particular) and other non-student populations can provide interesting insights for behavioural social scientists. Our research may fill this gap by providing results on the risk and ambiguity attitudes from African students' perspective. Results from studies with students are important as they can also help economists gain insight into the development of certain behaviour in the more experienced professionals (*farmers* in our case). As vocational students in our sample are future decision makers/experts and advisers to farmers; results from our study are important as the behaviour of this particular group of participants, might influence the advice they will provide. Of course in reality, advice on whether or not to adopt a certain drought tolerant variety might depend on various other factors that we did not control for in our experiment; however the results can provide a baseline. More often than not how we view things and process different information might potentially factor into what kind of advice we might provide in different scenarios. This notion of providing advice given uncertainty information is not tackled in our research but can be a subject for future study.

3.2. Literature review

Risk aversion

This section will provide a review of existing literature in experimental economics on risk and ambiguity attitudes of university/college students. Table 3.1 gives a summary of some of the studies which elicited the risk attitudes of students using Multiple Price List (MPL) format for different scenarios. Most studies in the table have been conducted in developed countries whilst very few have been undertaken with African students (see, Lammers and Van Wijnbergen, 2008; Tanner et al., 2005; Vieider et al., 2012). Studies generally indicate risk averse behaviour among students and those studies that compared the attitudes of students from different countries find African students more risk tolerant compared to others. Tanner et al (2005) found that students from Niger displayed more risk tolerance compared to the European and US students whilst Vieider et al. (2012) concluded the same with South African and Ethiopian subjects.

Perhaps, the most widely used method for eliciting risk aversion is the MPL experiment by Holt and Laury (2002b, HL henceforth); in which they provided subjects with a menu of ten paired lottery choices. Subjects had to make a choice between 2 options (Option A and B) in each of the 10 rows. Payoffs for Option A "safe choice" were \$2.00 (outcome A1) or \$1(outcome A2) and these were less variable than the potential payoffs for the "risky" Option B: \$3.85 (outcome B1) or \$0.10 (outcome B2). Probabilities for outcome A1/B1 increased from 0.1 to 1 in uniform increments of 0.1 whilst those for A2/B2 decreased from 0.9 to 0. The payoff matrix is shown in Table 3.2. A subject is expected to switch over to option B as they move down the table since the probability of the high payoff outcome will be increasing. Risk neutral participants are expected to switch from option A to B at decision row 5 and risk averse participants should switch between rows 6 to 10. Row 10 offers the high payoff with certainty hence by then everyone is expected to have switched. HL compared results of hypothetical and real payments and they also had a high payoff treatment where the payoffs were scaled by factors of 20, 50 and 90. Results from the HL study indicated general risk aversion with about a third of the students exhibiting such behaviour under low payoff. There was no distinction between hypothetical and real payoffs in the low payoff treatment. Scaling up the payoffs made no significant difference for hypothetical payoffs whilst participants become more risk averse when the high payoffs were real. No gender differences were found in the high payoff treatments but women were more risk averse under low payoffs. Our study uses a modified HL design to assess the risk and ambiguity attitudes of Zimbabwean college students. The experiment design is discussed in Section 3.3.

Table 3.2: Holt and Laury payoff matrix

Option A	**Option B**	**Expected payoff differences**
1/10 of \$2.00, 9/10 of \$1.60	1/10 of \$3.85, 9/10 of \$0.10	\$1.17
2/10 of \$2.00, 8/10 of \$1.60	2/10 of \$3.85, 8/10 of \$0.10	\$0.83
3/10 of \$2.00, 7/10 of \$1.60	3/10 of \$3.85, 7/10 of \$0.10	\$0.50
4/10 of \$2.00, 6/10 of \$1.60	4/10 of \$3.85, 6/10 of \$0.10	\$0.16
5/10 of \$2.00, 5/10 of \$1.60	5/10 of \$3.85, 5/10 of \$0.10	-\$0.18
6/10 of \$2.00, 4/10 of \$1.60	6/10 of \$3.85, 4/10 of \$0.10	-\$0.51
7/10 of \$2.00, 3/10 of \$1.60	7/10 of \$3.85, 3/10 of \$0.10	-\$0.85
8/10 of \$2.00, 2/10 of \$1.60	8/10 of \$3.85, 2/10 of \$0.10	-\$1.18
9/10 of \$2.00, 1/10 of \$1.60	9/10 of \$3.85, 1/10 of \$0.10	-\$1.52
10/10 of \$2.00, 0/10 of \$1.60	10/10 of \$3.85, 0/10 of \$0.10	-\$1.85

Table 3.1: Summary of risk experiments with students[a]

	County	Focus	Findings
(Andersen et al. 2006)	Denmark	risk aversion, discount rates	'Elicitation of risk attitudes is sensitive to procedures, subject pools, and the format of the MPL table, but the qualitative findings that participants are generally risk averse is robust. The elicitation of discount rates appears less sensitive to details of the experimental design.'
(Bassi, Colacito and Fulghieri 2013)	USA	effect of weather on risk aversion	'... bad weather increases risk aversion, while good weather conditions promote risk taking behaviour... also argued that weather affects risk-aversion through its impact on mood'
(Camacho-Cuena and Requate 2012)	Germany	pollution abatement	i) The performance of the collective fining mechanism is not affected by the subjects' risk preferences. ii) The performance of the random fining mechanism worsens in the presence of risk seeking subjects. iii) Under the tax-subsidy mechanism risk attitude has no significant effect, except for highly risk averse subjects which abate less.
(Eckel and Grossman 2008a)	USA	risk attitudes of male and female students	men were significantly less risk averse than women and both men and women predicted greater risk aversion for women
(Harrison et al., 2003)	USA	test of Expected Utility Theorem (EUT)	Subjects exhibit risk aversion in abstract lotteries and no risk loving behaviour. '...present evidence that EUT does not predict choice patterns well even after controlling for risk aversion. Overall, they 'find evidence of violations of EUT that cannot be easily dismissed by the free parameter of uncontrolled risk aversion.'
(Holt and Laury, 2002)	USA	risk aversion over different payoffs; hypothetical, real	About two-thirds of students exhibited risk aversion at the low payoff level. When real payoffs were used, risk aversion increased when pay-offs was scaled up by factors of 20, 50, and 90.
(Lammers and Van Wijnbergen 2008)	**South Africa** and USA	HIV, risk aversion and intertemporal choice	'...HIV positive agents and participants that perceive to have a high HIV contraction risk are less risk-averse. HIV positive participants had substantially lower discount rates.
(Lévy-Garboua et al. 2012)	France	risk aversion and framing affects	'Risk aversion was significantly higher in sequential than in simultaneous treatment, in decreasing and random than in increasing treatment, in high than in low payoff condition.' Inconsistencies were significantly higher in the sequential treatment than in the simultaneous one. The rate of inconsistencies was also higher in the increasing probability of winning and random treatment than in the decreasing probability of winning frame.
(Lusk and Coble 2005)	USA	genetically modified (GM) food	Most of the participants were risk averse. Elicited risk attitudes were significantly related to subjects' stated willingness -to-eat and purchase GM food, acceptance of GM food, and whether subjects had, at the time of the experiment, ever eaten GM food.'
(Schipper 2012)	USA	sex hormones and choice under risk	Subjects' were relatively more risk averse in the gain compared to the loss domain and relatively less women were risk seeking in the loss domain while in the gain domain women and men behaved the same. *Gains domain*: Risk aversion is negatively correlated with testosterone and positively correlated with cortisol, a stress hormone. In males, testosterone is negatively correlated with risk aversion. In females; cortisol, testosterone and progesterone are positively correlated with risk aversion. *Loss domain*: risk aversion is positively correlated with being female whilst testosterone and progesterone are positively correlated with risk seeking in females. *Consistency*: Testosterone is negatively correlated with 'consistency' in females, while estradiol is negatively correlated with 'consistency' in males.
(Schubert et al. 1999)	Switzerland	gender differences in financial decision making	In contextual decisions, there are no significant gender differences in risk attitude but in the abstract treatment there are significant differences; in the gain frame, females are more risk averse whilst in the loss frame, they are more risk seeking.
(Tanner et al. 2005)	**Niger,** China, USA, France	risk and time preference	Subjects from Niger displayed more risk tolerance compared to the European and US students. They also had significantly higher discount rates than the other subjects (China observations not included in analysis). In the risk preference experiment the behaviour of the Chinese and Nigerian subjects was not significantly different.
(Vieider et al. 2012)	30 countries incl. **South Africa** and **Ethiopia**	macroeconomic evidence of risk attitudes	Risk attitudes vary across countries. On a global level, risk seeking or risk neutral behaviour is just as frequent as risk aversion. GDP per capita explains about 36% of the between country variance in median risk attitudes and poor countries are more risk loving than the rich ones.

[a] studies use Multiple Price List (MPL) type experiments

Ambiguity aversion

This part highlights some of the studies focusing on *ambiguity aversion* that used students as subjects. As mentioned earlier, Ellsberg (1961) demonstrated *ambiguity aversion* and showed that individuals prefer to bet on a lottery with known probability (risk) as compared to one with unknown probability (ambiguity) even though the lotteries might have subjectively equivalent probability, thus violating the EUT. Ellsberg proposed two thought experiments that contradict SEU. In one of the experiments, an individual is presented with two urns containing red and black balls. Urn 1 contains red and black balls, but in an unknown proportion; whilst urn 2 has 50 red and 50 black balls. The participant is then asked which colour they prefer to bet on and from which urn if a ball is drawn at random; given they will receive $100 if they guess the correct colour and $0 otherwise.
Experiment results show that participants are indifferent on choosing between black and red but prefer to bet on the urn which has known probability compared to the ambiguous one. Evidence of this behaviour is presented in various studies (see., Pulford and Colman 2008, Camerer and Weber 1992, Keren and Gerritsen 1999, Liu and Colman 2009) using the Ellsberg urn or variations of it.

In Fox and Tversky (1995), the authors conducted various experiments with students to elicit ambiguity aversion using both within subject and between subject approaches. Their work led to the *comparative ignorance hypothesis* which states that, "ambiguity aversion will be present when subjects evaluate clear and ambiguous prospects jointly, but it will greatly diminish or disappear when they evaluate each prospect in isolation". Using the two-colour Ellsberg experiment described above (instead of balls they used poker chips); participants were asked their willingness to pay for each bet. Results showed strong evidence of ambiguity aversion when participants valued both the ambiguous and risky bets: they were willing to pay more for the risky bet compared to the ambiguous one. However, when the two bets were valued in isolation i.e. one group valued the risky bet alone whilst the other valued the ambiguous bet alone, ambiguity aversion disappears and in fact, participants were willing to pay less for the risky bet than for the ambiguous one. In another experiment, participants were asked to price bets that offered a fixed price if the future temperature in a given city was above/below a specified value. The subjects were from San Francisco hence they were 'familiar' with the weather there. Results indicated that participants were willing to pay more on average for the San Francisco bet when they evaluated both the clear and vague bet (both cities), however no such evidence was found when participants priced just one of the cities (one group priced San Francisco whilst the other one priced Istanbul (for similar results see., Chow and Sarin 2001; Fox and Weber 2002). In our study we used a between subject approach to assess risk and ambiguity attitudes. Participants were presented with only one experimental condition (either risk treatment or ambiguity treatment). We postulate that there will be significant differences in the behaviour of the two groups and that ambiguity aversion will not disappear when the ambiguity and risk attitudes of participants are elicited using a between subject approach. Charness, Gneezy and Kuhn (2012) summarise the issues surrounding within and between subject experimental designs. They conclude that the between subject approach is more conservative but has less power and '…both designs have their merits, and the choice of designs should be carefully considered in the context of the question being studied and in terms of the practical implementation of the research.'

Moore and Eckel (2003), provided students with a series of choices between a guaranteed amount and a lottery using a modified Holt and Laury (2002b) design. Different levels of ambiguity over: probabilities (for example 45-55% chance at winning $50), payoffs (for example 10% chance of winning $40–$60) and both probabilities and payoffs were used. Gambles were framed as 'lotteries' or as 'investments / insurance' decisions. Subjects then had to give valuations for known and ambiguous gambles over both possible gains and losses. A given lottery might have included; exact probability and exact payment, range in probability and fixed payment, exact probability and range in payoff and range in both probability and payoff. Results from this study indicate that participants exhibited ambiguity aversion in both the loss and gain frame. In the gain frame, participants preferred gambles which were framed as investment as opposed to lotteries. There were no significant gender differences for risk/ ambiguity aversion in the gain frame, however differences were found in the loss domain with women more risk/ambiguity seeking compared to men. The Moore and Eckel method is almost similar to ours however they use a within subject approach whilst we use a between subject one.

Models for optimism and pessimism

A number of models have been put forward to explain decision making under ambiguity. In this section we give a brief overview of some of the models that take into account pessimistic or optimistic behaviour. Do participants presented with the ambiguity treatment make choices based on the minimum, maximum, centre or anything between the provided ranges? For example in one of the decisions, the probability of drought is provided as between 0 and 10%. If a participant assumes the probability is 0% then they are expected not to adopt the drought tolerant variety, whereas if they take the maximum of 10% they may/may not adopt. At 0% participants are *optimistic* that a drought will not occur whilst at the other extreme end they are *pessimistic* and expect the worst. It is however possible that as the minimum and maximum values of the range increase, participants may change their decision making criteria, and instead of making decisions based on the minimum they will change to maximum or anywhere within the range. Our analyses will try and model decision criteria at the extremes. When asked how they made their decisions; a couple of students presented with the ambiguity treatment indicated that they calculated the average of the range. Note: Although we focus only on participants presented with the ambiguous treatment, it is also possible that those provided with the risk treatment could have adjusted the point estimate they were given, upwards or downwards, however in our analysis we will only use the former. Whether or not risk participants adjusted the point estimates they were provided with, is beyond the scope of this study but can be a subject for future research. A few theoretical models that take optimism or pessimism into account are described below.

a) Anchoring and adjustment model (Einhorn and Hogarth 1985) (Einhorn and Hogarth 1986)

In this model, Einhorn and Hogarth propose that when presented with an ambiguous situation, a decision maker (DM) uses an anchoring and adjustment strategy. The initial probability which can serve as an anchor can come from different sources which include the best guess of experts or it may just be a probability that is salient in the memory. Depending on whether or not a DM is pessimistic or optimistic about the probability of the given event occurring, they will adjust the anchor probability upwards or downwards via a mental simulation process. Decision making or choice under ambiguity will therefore depend on the degree of adjustment above or below the anchor. Consider a participant from our experiment who is told that the probability of drought is between 40-50% and one from the risk treatment who is told the probability is 45%. If we assume that 45% is the anchor, the participant in the ambiguity treatment is potentially forced to consider probabilities higher than 45% and also lower than 45%. '...Einhorn and Hogarth's (1985) model would appear to predict even less ambiguity avoidance when interval estimates are present and made salient, since decision makers may be more likely to be aware of the possibility of probabilities above...' the anchor (Highhouse 1994).

b) Choquet expected utility (Schmeidler 1989)

Choquet expected utility theory models uncertainty using a non-additive probability function called capacity (replaces the additive measure of SEU). A capacity therefore represents the DM's beliefs about the likelihood of uncertain events and assigns greater weight to event *A* than *B when* *B* is a subset of *A*, while a probability measure must assign weights that are additive across events that are mutually exclusive. Hence, one can calculate the expected utility of an act with respect to the non-additive probability using the Choquet integral. Different ambiguity attitudes can be captured through the non- additivity of the capacity with a concave capacity reflecting optimism whilst a convex one reflects pessimism. This model allows for more weight to be assigned to the least favourable outcome, thus discounting the most favourable events leading to pessimistic behaviour.

c) Maxmin model (MEU) - (Gilboa and Schmeidler 1989)

The model maximises the minimum of the expected utility over the possible distribution of probabilities. The DM chooses any act g and evaluates it by maximising his/her utility whilst assuming the worst case probability distribution. The maxmin model can be represented as: $MEU(g) = min_{p \in P} \sum_{s \in S} p(s)U(g(s))$; where $U(g(s))$ is the expected utility of the lottery over X that act g generates in state s. A maxmin DM therefore exhibits extreme pessimistic behaviour and is overly ambiguity averse. On the other hand, under maximax criterion, the DM is optimistic and finds the maximum payoff for each of the possible states and chooses the option with the best outcome. The amount of ambiguity aversion cannot be measured by this model because of the absence of an 'objective' reference for the set of priors (Etner, Jeleva and Tallon 2012).

d) α-Maxmin Expected Utility (Ghirardato, Maccheroni and Marinacci 2004)

The α-MEU model is an extension of MEU and includes α, a function which measures ambiguity aversion by taking a weighted combination of the best and worst distributions. DMs weigh the least and maximum expected utility such that: $MEU(g) = \alpha min_{p \in P} \sum_{s \in S} p(s)U(g(s)) + (1-\alpha) max_{p \in P} \sum_{s \in S} p(s)U(g(s)); \alpha \in [0,1]$. When $\alpha = 1$, the model reduces to MEU and DM is pessimistic; when $\alpha = 0$, model reduces to maximax.

3.3. Experimental design

Our experiment followed a (Holt and Laury 2002b) design and involved making a series of 40 choices from two options. The experiment was slightly modified such that participants had to choose the risky option for the first few decisions before switching to the safe option. In the original HL experiment, participants were expected to choose the safe option in the first series of decisions before switching to the risky ones. The experiment involved two parts, each with 20 decisions. Typical HL experiments have 10 binary choices. Participants were asked to choose whether or not to adopt a new drought tolerant (DT) crop variety after being told the exact probability of a drought occurring (for example 40% probability of drought) or the range (for example 20-60% probability of drought). Adoption was the safe choice (Lottery A) whilst non-adoption was the risky alternative (Lottery B). The payoffs presented to participants for the 2 parts are shown in Tables 3.3(a) and (b). The experiment instructions are in Appendix 3.1. Note that for Part 2 of the experiment the safe option was a sure bet (participants would get a payoff of 6 whether or not a drought occurred) whilst the risky bet is the same as that in Part 1.

Table 3.3(a): Payoffs for part 1 of the experiment

Choice (tick)		Drought	Rain
	Adopt	4	6
	Do not adopt	0	10

Table 3.3(b): Payoffs for part 2 of the experiment

Choice (tick)		Drought	Rain
	Adopt	6	6
	Do not adopt	0	10

Participants were presented with *either* the exact probabilities (*all* 40 decisions showed the exact probability) *or all* 40 decisions showed the range of probabilities and not a mixture; hence there were two groups of participants. A between subject rather than a within subject approach was used. Participants were also informed that the new DT crop variety could do well in both rainy and drought conditions. The payoffs were fixed across the decision rows whilst the probabilities varied. For the safe choice, there was a small difference (no difference in part 2) between the high and low pay off whilst the difference for the risky treatment was more variable. The participants first completed 20 decisions in part 1 of the experiment before completing 20 more decisions in part 2. Decision 20 in the two parts was a test to check if the participants understood the experiment. In these decisions, the probability of drought was 100%. As shown in Table 3.3 the choice would have been between an expected value of 0 and 4 (0 and 6) in part 1 (part 2), hence participants were expected to choose the safe option (adopt) in these decisions as non adoption would have resulted in a payoff of zero.

The ambiguous lotteries were derived from the risk lotteries such that for a risk lottery which offered a payoff of x with probability p, the equivalent ambiguous lottery would offer the same payoff x with probability which is between p_{min} and p_{max} (where $p_{min} = p - r$ and $p_{max} = p + r$, r = 5%= probability width interval) and $p = (p\_min + p\_max)/2$, for example at 30% probability of drought, the risk option (lottery A) would be (4,30%;6,70%) whilst the corresponding ambiguous lottery would be (4, [25%,35%]; 6[otherwise]). Simply, the probability of the risky treatment was the centre of the range in the ambiguous treatment for each decision choice. Table 3.4 shows the expected values of the two lotteries for parts 1 and 2 of the experiment. The expected values were not shown to the participants.[27]

Individuals were expected to choose Lottery B for the first few decisions before switching to lottery A as the probability of drought increases. If risk neutral, participants will choose lottery B which has the higher expected payoff until decision 10 (decision 8) for part 1(part 2) and then switch to A. At decision 10(decision 8) the expected value of lottery A= expected value of lottery B. Only

[27] Providing expected values may anchor the participants and thus influence and bias their preferences towards risk neutrality. Harrison and Rutström (2008) note the need for more empirical studies to assess the effect of providing EV information and suggest that some subjects may be trying to calculate the EV anyway, "so providing them avoids a test of the joint hypothesis that the subjects can calculate EV in their heads and will not accept a fair actuarial bet. On the other hand, providing them may cue the subjects to adopt risk-neutral choices."

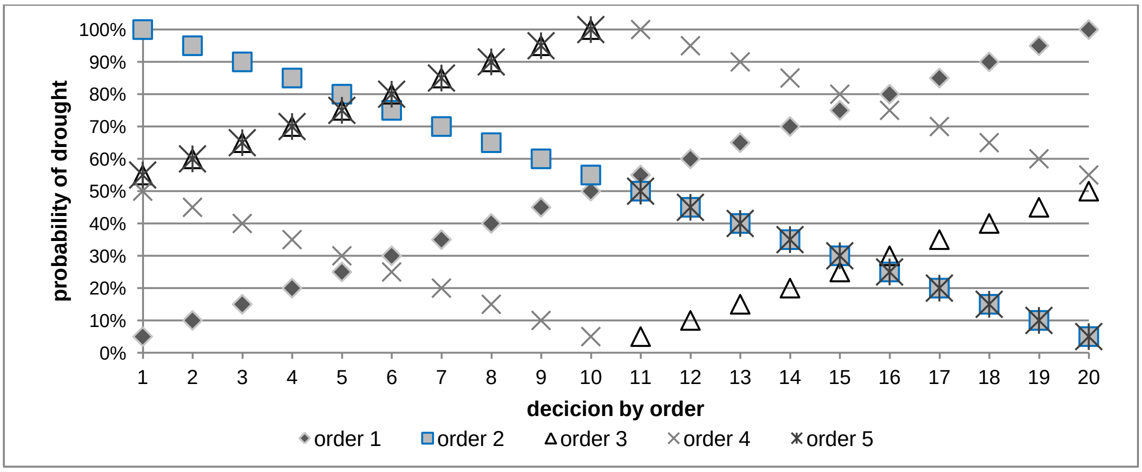
risk seeking participants will choose lottery B (risky) at decision 19 and risk averse individuals will choose lottery A in decision 1. An individual's risk/ambiguity attitude can be measured by the number of safe choices as in Holt and Laury (2002).

Table 3.4: Expected values of the two lotteries

	Probability of drought		Part 1			Part 2		
Decision	**Risk**	**Ambiguity**	**EV^A**	**EV^B**	**EV^A - EV^B**	**EV^A**	**EV^B**	**EV^A - EV^B**
1	5%	0-10%	5.9	9.5	-3.6	6.0	9.5	-3.5
2	10%	5-15%	5.8	9.0	-3.2	6.0	9.0	-3.0
3	15%	10-20%	5.7	8.5	-2.8	6.0	8.5	-2.5
4	20%	15-25%	5.6	8.0	-2.4	6.0	8.0	-2.0
5	25%	10-30%	5.5	7.5	-2.0	6.0	7.5	-1.5
6	30%	25-35%	5.4	7.0	-1.6	6.0	7.0	-1.0
7	35%	30-40%	5.3	6.5	-1.2	6.0	6.5	-0.5
8	40%	35-45%	5.2	6.0	-0.8	6.0	6.0	0.0
9	45%	40-50%	5.1	5.5	-0.4	6.0	5.5	0.5
10	50%	45-55%	5.0	5.0	0.0	6.0	5.0	1.0
11	55%	50-60%	4.9	4.5	0.4	6.0	4.5	1.5
12	60%	55-65%	4.8	4.0	0.8	6.0	4.0	2.0
13	65%	60-70%	4.7	3.5	1.2	6.0	3.5	2.5
14	70%	65-75%	4.6	3.0	1.6	6.0	3.0	3.0
15	75%	70-80%	4.5	2.5	2.0	6.0	2.5	3.5
16	80%	75-85%	4.4	2.0	2.4	6.0	2.0	4.0
17	85%	80-90%	4.3	1.5	2.8	6.0	1.5	4.5
18	90%	85-95%	4.2	1.0	3.2	6.0	1.0	5.0
19	95%	90-100%	4.1	0.5	3.6	6.0	0.5	5.5
20	100%	100%	4.0	0.0	4.0	6.0	0.0	6.0

The order of the decisions was randomised for part 1 of the experiment. The probability of a drought occurring was either increasing from 5% to 100% in the last decision, decreasing from 100% to 5% or was presented in random order with differences in probabilities of 5% between subsequent rows (for the equivalent ambiguity treatment ranges refer to Table 3.4). The different orders are represented in Figure 3.1. For part 2 of the experiment, the order was not randomised and probability of drought increased from 5 to 100 % (the order was not randomised to reduce 'noise').

Figure 3.1: Decision orders for part 1



Variations and randomisation in the presentation of probabilities can potentially induce different reference points which in turn, influence how individuals make their decisions. The reference points therefore can serve as an *anchor.* Only one study was found that used different orders in an MPL format for measuring risk preferences and none for ambiguity. Lévy-Garboua et al. (2012) investigate whether changing the order of probabilities of winning has any impact on inconsistency by replicating the Holt and Laury (2002) design, using orders ranked as increasing, decreasing or random.[28]

- *Recruitment of participants and experimental administration*

Students were recruited from 2 vocational agricultural colleges (Esigodini and Gwebi). The latter is in a dry region of the country whilst the former is located in a region that receives relatively normal to above normal rainfall. A total of 61 students (31 from Esigodini and 30 from Gwebi) participated in the experiments. The mean age of the students was 27.7 years, with a range between 19 and 45 years. Just over half (50.8%) were female and about 45.9% of the students were single. The students were chosen at random using yes/no cards for separate male and female students. All the students at the college at the day of the experiment were gathered in a room and brief introductions were made. The purpose of the gathering was explained and we asked for volunteers who wanted to leave but everyone was interested in participating in the study. We separated the male and female students and had them pick yes/no from a box. Those who picked 'yes' remained in the room and the experiment was explained to them whilst those who picked 'no' were discharged. The experiment instructions (which were written in English)[29] were then handed out to the participants. After handing out the instructions, the researcher read aloud and went through the instructions with all the participants. Students were given time to read the instructions on their own and asked to raise their hands if they had any questions. After making sure participants understood the instructions, experiment decision sheets for Part 1 were given out. After everyone had finished Part 1 of the experiment, Part 2 decision sheets were similarly distributed. At the end of the experiment, participants were asked to fill out a brief questionnaire on individual characteristics and risk perceptions and payments were made. The payment method is described below.

[28] Other studies that use randomised order for measuring discount rates are: Eckel et al, 2005; Kirby and Maraković, 2006
[29] English is one of the official languages in Zimbabwe and the mode of instruction at vocational colleges. Explanations were also given in the native languages (Shona and Ndebele) for clarification.

- *Payment procedure*

At the end of the experiment, two rounds were chosen at random for payment. Participants were told beforehand that the average of 2 random rounds (one from part 1 and the other one from part 2) would be chosen to determine their payoff and that this depended on their individual decisions. To choose the payment decision, pieces of paper labelled 1 to 20 were used and put in a hat. One of the students was asked to choose one paper in order to remove experimenter bias. If for example a paper written ‘18’ was chosen, decision 18 (with 90% chance of drought) would be used for payment. After the decision choice, to find out hypothetically if it would be a good rainy season / drought, 10 papers were used: from the case above, 9 were clearly labelled ‘drought’ and 1 was labelled ‘rain’. A participant was then asked to pick one paper from the hat at random to determine if the payoff would be under drought/rain conditions. The participant was also asked to verify if there were 20 (10) decisions in the hat in the first decision choice (second) in front of all the participants.

3.4. Empirical Strategy

The study assumes expected utility theorem (EUT) and constant relative risk aversion utility (CRRA) following Harrison and Rutström (2008). The CRRA function is represented by:

$$U(x) = x^{1-r}/(1-r) \qquad (1)$$

where x = payoff/lottery prize and r = CRRA coefficient.

$r = 0$ denotes a risk neutral participant, whilst a risk loving and risk averse participant will have $r < 0$ and $r > 0$ respectively. Our experiment has two possible lottery outcomes denoted by k, with probabilities, $p(k)$ which are specified by the experimenter. If we assume that EUT holds for the participants’ choices, the expected utility which is the probability weighted utility of each outcome in each lottery (i) will be:

$$EU_i = \sum_{k=1,2} [p(k) \times U(k) \qquad (2)$$

The choice of lottery A or B (adopt or do not adopt) depends on the following latent variable:

$$\nabla EU = \frac{EU_A - EU_B}{\mu} \qquad (3)$$

where EU_A = expected utility from lottery A, EU_B = expected utility from lottery B and μ is the Fechner error parameter which accounts for participant behavioural errors, $\mu \sim N\ (O, \sigma^2)$.

We use a cumulative normal distribution function, $\Phi(\nabla EU)$ such that,$(\nabla EU) = Pr(EU_A - EU_B) > 0$, measures probability when lottery A is chosen over lottery B and $[1 - \Phi(\nabla \mathrm{EU})]$, measures probability when lottery B is chosen. Hence, the log likelihood function which will be estimated is:

$$InL(r, \mu; y, \boldsymbol{X}) = \sum_i l_i = \sum_i [In\ \Phi(\nabla EU) \times \boldsymbol{I}\ (y_i = 1) + (In\big(1 - \Phi(\nabla EU)\big) \times \boldsymbol{I}(y_i = 0))] \quad (4)$$

Where $I\ (.)$ is an indicator function, $y_i = 1(0)$ indicates choice of lottery A (B) in decision i and X = vector of individual characteristics e.g. sex, age, marital status and so forth.

3.5. Results

The experiment results will be presented as follows:

a) Inconsistency
b) Number of safe choices
c) Probability of choosing safe option
d) Switch point , CRRA
e) Factors determining risk/ambiguity attitudes using other models
f) Risk perception measure

3.5.1. Inconsistency

Thirty-one participants were presented with the risk treatment, whereas 30 were presented with the ambiguous one. Twelve and 10 of the 61 participants were inconsistent in parts 1 and 2 of the experiment respectively (Table 3.5). These individuals switched back and forth between the rows, probably implying inconsistent preferences or a misunderstanding of the experiment instructions. Eight of the students were inconsistent in both parts 1 and 2. Inconsistency might also have been due to indifference between the choices or mistakes when ticking the options- the experiment was paper based and participants were asked to choose their options by ticking which one they preferred (not all the questions were presented on one sheet thus perhaps contributing to mistakes)

Table 3.5: Inconsistent participants by treatment and order

		n	**Number inconsistent**	**% inconsistent**
All	Part 1	61	12	19.7
	Part 2	61	11	18.0
Risk treatment	Part 1	31	6	19.4
	Part 2	31	6	19.4
Ambiguity treatment	Part 1	30	6	20.0
	Part 2	30	5	16.7
Order (part 1)	1	17	2	11.8
	2	12	3	25.0
	3	11	4	36.3
	4	9	2	22.2
	5	12	1	8.33

Lévy-Garboua et al. (2012) found that a simultaneous frame increased the rate of consistency among subjects compared to a sequential one. They attribute this to 'more information' being provided by the simultaneous frame as it shows the whole menu of lotteries thus maybe inducing transparency. In our case, although participants were given all decisions in a booklet, there were a few decisions on one page, and then they had to turn over the pages thus perhaps inducing some errors which might have been reduced if all decisions were on one page. The rate of inconsistency is higher in part 1 of the experiment for all students and those presented with the ambiguity treatment. Recall that orders were only randomised for part 1; for part 2, order 1 was used for all participants (this was done to reduce the noise brought about by randomisation). The percentage of inconsistent participants is slightly higher for the ambiguity treatment compared to the risk treatment for part 1 (20% vs. 19.4%). The differences in inconsistency for all groups discussed above are not statistically significant using a Mann-Whitney test.[30]

Question: is there a significant difference in inconsistency between the two parts and the different orders?

When analysed by order, order 3 has the highest number of inconsistencies

[30] p= 0.739 for part 1 and 2,p= 0.95 for risk and ambiguity (part 1), p=0.787 for risk and ambiguity (part2), p= 0.655 for part 1 risk and part 2 risk, p=1 for part 1 ambiguity and part 2 ambiguity

(around 36%) followed by order 2 (decreasing probability of drought). Mann Whitney tests indicate no statistically significant differences in inconsistency between the orders. The results for tests on other orders are shown in Appendix 3.2. Random effect probit models were run to determine factors affecting inconsistency. The dependent variable was binary, 1= inconsistent and 0= consistent. Results are presented in Table 3.6. The regression results indicate that, order 1 (increasing probability of drought) improves consistency relative to order 2 (decreasing probability of drought) and order 3. Order 1 was used as the reference point. In contrast, Lévy-Garboua et al. (2012) found more inconsistencies in the increasing compared to the decreasing frame. Model (2) included other factors that were part of the experiment design and in part 1 of the experiment, participants were more likely to be inconsistent compared to part 2. The latter was presented to all participants using an increasing order and the payoff for adoption was the same whether or not a drought occurred and was higher than that in part 1. Although not all payoffs were increased by a similar scale this result indicates that a higher certain payoff perhaps encourages consistency. Results from experiments by Lévy-Garboua et al., 2012 showed that the inconsistency level is significantly reduced by increasing payoffs. They used the HL experiments where payoffs are increased by a factor of x10. When demographic variables are included in our model, *age* and *single* are significant variables. The variables have positive coefficients indicating that the older participants are more likely to be inconsistent as are the single participants.

Table 3.6: Determinants of inconsistency

	(1)	(2)	(3)
order 2	**2.705*** **	**2.814*** **	**1.840***
	(0.804)	(0.846)	(1.003)
order 3	**1.839** **	**2.247*** **	0.313
	(0.802)	(0.851)	(1.035)
order 4	0.003	-0.166	-0.440
	(0.695)	(0.823)	(1.040)
order 5	0.230	0.394	0.470
	(0.757)	(0.958)	(1.015)
risk treatment		-0.685	-0.921
		(0.563)	(0.744)
part 1		**0.259** **	**0.268** **
		(0.128)	(0.130)
female			-0.962
			(0.718)
age			**0.249*** **
			(0.068)
single			**1.564***
			(0.908)
constant	-6.773***	-5.900***	-14.86***
	(0.460)	(0.639)	(2.675)
ln (σ_u^2)	3.641***	3.511***	4.040***
	(0.337)	(0.370)	(0.342)
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1			

Another random effects probit model was run with the independent variables for orders as; increasing (order 1), decreasing (order 2) or random (orders 3, 4 and 5 together). This was done to find out if there were any significant differences between the random order and the monotonically increasing order. Table 3.7 indicates that the increasing frame increases consistency relative to the random and decreasing probability of drought (models 5 and 6) frame. Participants who were presented with the risk treatment were more consistent compared to those presented with the ambiguity treatment. Ambiguity was presented as a range of probabilities hence possibly inducing some bias. As was the case in the previous models, demographic variables age and being single have positive coefficients. The gender of the respondent now becomes a significant determinant of inconsistency. Controlling for all variables, female participants are more consistent compared to their male counterparts.

Table 3.7: Determinants of inconsistency-2

	(4)	(5)	(6)
random frame	0.857	1.828***	1.768**
	(0.580)	(0.623)	(0.743)
decreasing frame	2.054**	3.596***	4.740***
	(1.017)	(0.803)	(1.087)
risk treatment		-1.045**	-1.547**
		(0.525)	(0.677)
part 1		0.260**	0.268**
		(0.128)	(0.130)
female			-1.157*
			(0.700)
age			0.344***
			(0.071)
single			1.967**
			(1.003)
constant	-5.773***	-6.908***	-18.03***
	(0.487)	(0.574)	(2.778)
ln (σ_u^2)	3.424***	3.654***	3.818***
	(0.359)	(0.352)	(0.347)

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

3.5.2. Number of safe choices

Figure 3.2 summarises distribution of the number of safe choices by part and treatment. The number of safe choices ranged from 5 to 20 and there are differences in the median, upper and lower quartiles for those shown the risk and ambiguity treatment.

Figure 3.2: Distribution of number of safe choices

The average number of safe choices for parts 1 and 2 were 15.1 and 15.5 respectively for participants who were consistent[31] in both parts. Wilcoxon signed-rank test shows that this difference is significant (z=-1.97 and p<0.05). Part 2 of the experiment involved making choices between a certain outcome and a lottery with probability of drought increasing in increments of 5%.

Results on t-tests for other categories are presented in Table 3.8(a). Participants who were shown the ambiguity treatment on average chose more safe options compared to those presented with the risk treatment, in both parts. The average number of safe choices for part 2 of the experiment is significantly higher for participants presented with ambiguity compared to those presented with the risk treatment at the 10% level (p=0.057). Male participants made a higher average number of safe choices compared to their female counterparts in both parts. This difference is statistically significant in part 2. Married students chose a higher average number of safe choices in both parts. Students, who indicated that they were household heads, significantly choose more safe options compared to the non household heads (p< 0.1) in part 2 of the experiment. All the household heads were male. Almost similar results are found when the full sample of participants was analysed[32]. The results are presented in Appendix 3.3. When the average number of safe choices between part 1 and part 2 are compared, there are significant differences within some of the groups (Table 3.8b). For most of the categories, part 2 has a higher average number of safe choices compared to part 1

[31] If inconsistent participants are included the average safe choices are 14.5 and 15.2 for part 1 and 2 respectively (z=-2.11, p<0.05).
[32] A Kolmogorov-Smirnov test for equality of distribution functions for both parts indicate that there are no differences in the distribution of the number of safe choices between a sample with all participants and one with just the consistent participants (p=0.231 and 0.140 for parts 1 and 2 respectively).

except for the risk treatment and for household heads; however this is not statistically significant. Signed rank tests show significant differences in the average number of safe choices for Gwebi College, participants who were presented with the ambiguity treatment, females, the single and those who indicated they were not household heads. Results for all participants are presented in Appendix 3.3.

Table 3.8(a): Average number of safe choices for different groups (consistent in either part)

		Part 1			Part 2		
		Mean	**t**	**p**	**Mean**	**t**	**p**
college	Esigodini	15.40	0.899	0.373	15.63	0.462	0.646
	Gwebi	14.33			15.04		
treatment	Risk	14.16	1.243	0.220	14.36	1.607	0.115
	Ambiguity	15.63			16.36		
sex	Male	15.58	1.167	0.249	16.68	1.902	**0.063**
	Female	14.20			14.32		
marital status	Married	15.12	0.423	0.674	15.70	0.585	0.562
	Single	14.61			14.96		
household head	No	14.21	-1.670	0.105	14.66	-1.910	**0.065**
	Yes	16.25			17.00		

Table 3.8(b): Average number of safe choices for different groups-part 1 vs. part 2 (consistent in both parts 1 and 2)

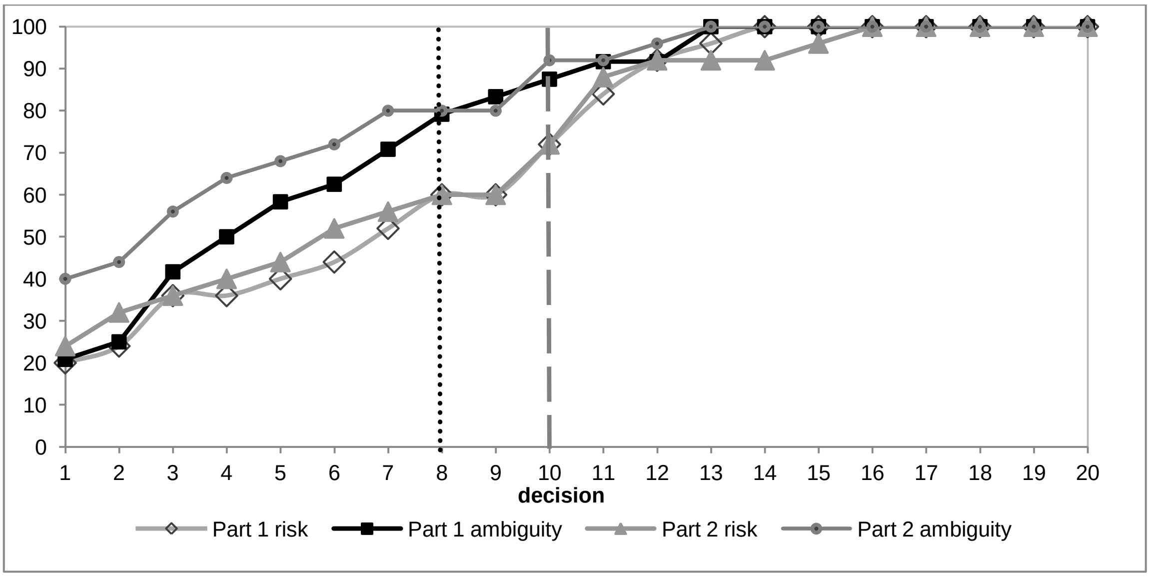
				t-test		Wilcoxon rank	signed
		part 1	**part 2**	**t**	**p**	**z**	**p**
college	Esigodini	15.77	16.00	-0.251	0.804	-1.002	0.316
	Gwebi	14.52	14.96	-0.778	0.444	-1.734	**0.083**
treatment	Risk	14.52	14.00	0.624	0.539	-0.263	0.792
	Ambiguity	15.77	17.00	-2.169	**0.042**	-2.691	**0.007**
sex	Male	16.30	16.50	-0.228	0.822	-0.969	0.333
	Female	14.20	14.64	-0.692	0.495	-1.817	**0.069**
marital status	Married	15.43	15.65	-0.248	-0.846	-1.031	0.303
	Single	14.82	15.27	0.806	0.430	-1.814	**0.070**
household head	No	14.34	14.94	-1.165	0.253	-2.477	**0.013**
	Yes	17.08	16.77	0.234	0.819	-0.071	0.944

According to Gilboa and Schmeidler (1989), we expect participants presented with the ambiguous treatment to switch to the safe option one decision earlier than those presented with the risky treatment if they are pessimistic (i.e. if they take the lower end of the range as the true probability). However, participants presented with ambiguity in our sample are even more pessimistic and choose the safe option on average at least 1 decision earlier in part 1 of the experiment. In part 2, they switch to the safe option on average about 2 decisions earlier. If we use the median, ambiguity participants chose 2.5 and 3 more safe choices for parts 1 and 2 respectively. The differences for risk and ambiguity might indicate that the latter participants are more pessimistic than would be expected. The median is probably a better measure and more robust since the distribution of the number of safe choices is skewed. Further statistical analysis will be done in section 3.5.4 (b) to assess the possible pessimistic behaviour of participants presented with the ambiguity treatment.

Proportion of safe choices by decision, part and order

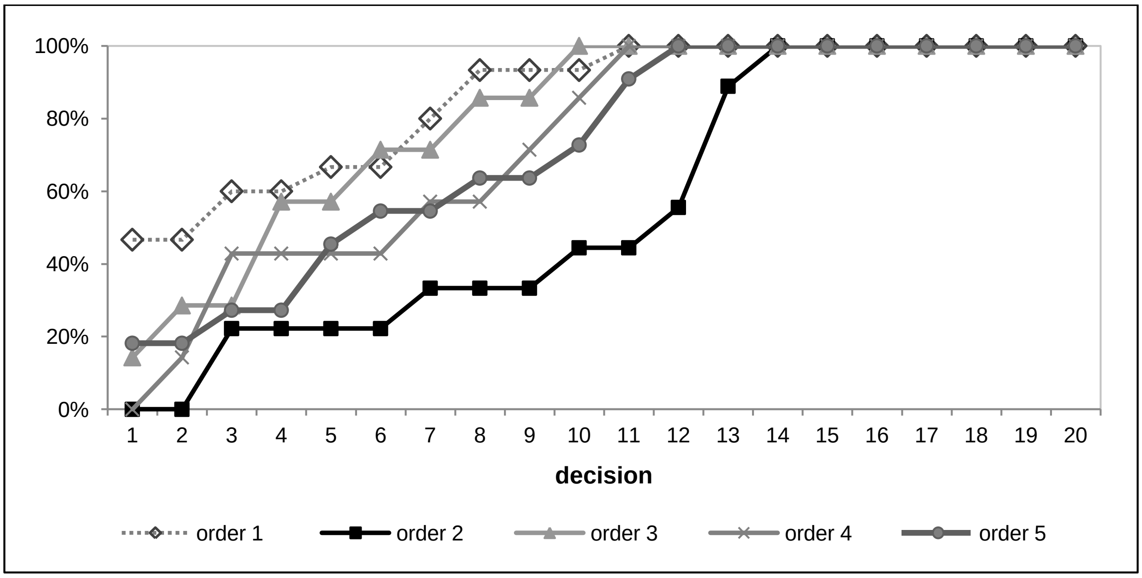
Figure 3.3 shows the proportion of consistent students choosing the safe option for each decision[33]. The figure indicates an inclination towards risk aversion by most students as a greater proportion is on the left side of the risk neutral prediction dashed lines (thick line at decision 10 for part 1 and thin line for part 2). At these decisions, $EV^A = EV^B$. From our experimental design, the risk neutral line shows that a participant who is neutral would choose the risky lottery (B) when the expected value of the lottery (EV^B) is higher than that of lottery A- safe option (EV^B) and then switch when, $EV^A > EV^B$.

Figure 3.3: Percent choosing safe option for each decision



[33] Decision 1, 2,…, 20 in this case and in all the subsequent analyses denotes choices with increasing probability of drought (i.e. 5%, 10%,…,100% respectively for risk and for ambiguity refer to Table 3.4).

Figure 3.4: Proportion choosing safe option by order- Part 1



The proportion of participants choosing the safe option is higher for those presented with the ambiguity treatment compared to those presented with risk for almost all decisions. This indicates ambiguity averse behaviour on the part of the students. They are avoiding the ambiguous probability by choosing to adopt. When analysed by order, a higher percent of participants shown order 1 choose more safe options compared to the other orders for almost all decisions (Figure 3.4). The proportion of students who choose the safe option for order 2 was lower than for the other orders until decision 14 (at which point all participants choose the safe option) and subjects in this category tended to behave closer to the expected, by choosing the risk option in decisions 1 and 2.

The different orders seem to induce some anchoring effects. The value that an individual can put on an item can differ depending on what it’s compared to and if a choice set is used; the order in which the information is presented can also affect decision making. Andersen et al. (2006) note that the MPL format might encourage participants to have a psychological anchoring effect towards the centre and they suggest randomisation of the orders as a possible solution, although this may add unnecessary noise to the data. Randomising the orders might also increase inconsistencies. The monotonically decreasing probability of drought frame (order 2) had the lowest proportion of participants choosing the safe option all decisions before decision 14 (70% probability of drought) where all participants adopt.

Table 3.9: Proportion choosing safe option as experiment progressed

question	order 1	order 2	order 3	order 4	order 5
1	47%	100%	100%	86%	91%
2	47%	100%	100%	71%	100%
3	60%	100%	100%	57%	100%
4	60%	100%	100%	57%	100%
5	67%	100%	100%	43%	100%
6	67%	100%	100%	43%	100%
7	80%	100%	100%	43%	100%
8	93%	89%	100%	43%	100%
9	93%	56%	100%	14%	100%
10	93%	44%	100%	0%	100%
11	100%	44%	14%	100%	73%
12	100%	33%	29%	100%	64%
13	100%	33%	29%	100%	64%
14	100%	33%	57%	100%	55%
15	100%	22%	57%	100%	55%
16	100%	22%	71%	100%	45%
17	100%	22%	71%	100%	27%
18	100%	22%	86%	100%	27%
19	100%	0%	86%	100%	18%
20	100%	0%	100%	100%	18%

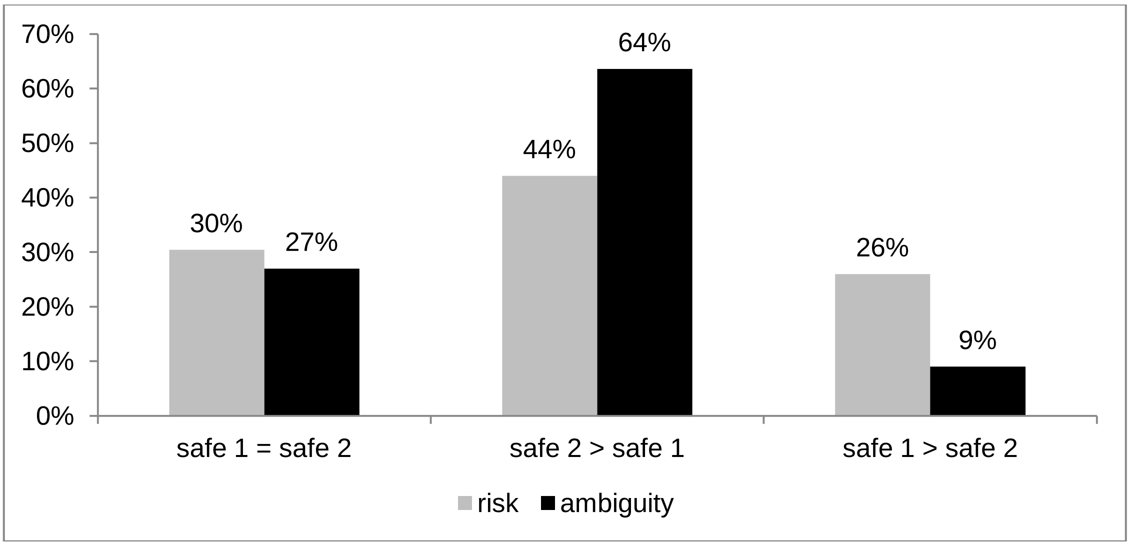
This result suggests that participants used 100% of drought as the reference point and by the time they reached for example the decision with 40% of drought they would not put the same weight on it as someone who perhaps started with 5% probability of drought (increasing frame). The latter would perceive 40% to be high compared to 5% whereas with an anchor of 100% it would seem like a low value. To understand this more clearly, Table 3.9 shows the proportions choosing the safe option as the experiment progressed. Recall that orders 3 and 5 started with 55% probability of drought in increasing order and as such almost all participants choose the safe option. Interestingly order 4 starts with an equally likely probability (50%) and a lower proportion of participants in this group choose to adopt in the first decision compared to order 3 and 5. A drop in the probability to 5% from 100% for order 3 significantly reduces the proportion choosing the safe option to just 14%, whilst a reduction to 50% in order 5 reduces the proportion to just below three quarters. By the time order 3 participants reach 50% probability, all of them choose the safe option since their reference point is perhaps 5% in the middle of the table. Similarly, for order 4, by the time participants get to 5% probability after starting with an anchor of 50%, none will choose the safe option at such low probability whereas in decision 1 where the anchor is 5%, close to half of the participants choose to adopt. It is possible that when participants reached the middle they readjusted their anchor especially for orders 3, 4 and 5. Figures for risk and ambiguity are presented in Appendix 3.4. The same reasoning explained above can be used, however the results for the separate treatments may not be representative, because of the small sample sizes within each order hence they must be treated with caution.

Question: is there a significant difference in the proportion choosing the safe option between the two parts and the different orders?

In part 1, Wilcoxon Mann-Whitney tests reject the null hypothesis of equal means between the orders in both part 1 with $p<0.01$ except for the differences between order 1 and 3; and order 4 and 5 where we fail to reject the null. In part 2, there are significant differences in the mean number of safe choices between the orders except between orders 4 and 5. When the orders are analysed as increasing, decreasing and an aggregation of the random order, Wilcoxon Mann-Whitney tests also reject the null hypothesis of equal means between the orders.

Analysis was also done to assess if participants choose lower, higher or equal number of safe options in either parts (Figure 3.5). Safe 1(safe 2) represents the number of safe choices in part 1 (part 2), thus safe 2>safe 1 denotes that the number of safe choices in part 2 were strictly higher than those in part 1 and vice versa. Most of the participants choose more safe options in part 2 compared to part 1 despite the treatment (44% for risk and 64% for ambiguity).

Figure 3.5: Comparison of number of safe choices for parts 1 and 2



If we use the number of safe choices as a measure of risk/ambiguity aversion, the comparison indicates that most participants were perhaps more risk and ambiguity averse in part 2 of the experiment. Among those who chose the same number of safe options in both parts (safe 1=safe 2); half and around 43% of those presented with the risk and ambiguity treatment respectively, chose the safe option in all decisions. This can probably explain the high percentages in that category. We would expect none of the participants to choose more safe choices in part 2 compared to part 1, but around 26% and 9% of those shown the risk and ambiguity treatment, act 'irrationally'. However, the reason why this may be happening is because students were 'hedging'; only one decision from each part was used as payment, hence if participants would have made risky choices in the first part, they may decide not to take so much risk in the second part.

3.5.3. Probability of choosing safe option

Question: What are the factors determining the probability of choosing the safe option?

Table 3.10 shows the determinants of choosing the safe option after a probit model. Female participants are less likely to choose the safe option. The probability of a safe option being chosen is higher for part 2 which had a higher payoff for the risky option, for those presented with the ambiguity treatment. Relative to the increasing frame, the probability of choosing the safe option decreases with the random and decreasing frame. An increase in the probability of drought occurring increases the probability of choosing the safe option, with high predictive power for the ambiguous treatment compared to the risk one. When an interaction term between treatment and probability is included, the coefficient is highly significant (z=-4.08, p=0.00); indicating that the regression coefficient on *probability* for ambiguity is significantly higher than the one for risk. Similarly, when an interaction between part and treatment is included in the model for all participants; z=2.27 and p=0.02 indicating the probability of choosing the safe option is significantly less for risk part 1 compared to risk part 2 and ambiguity (both parts). In both cases, variables which were significant in model (7), remain significant, except treatment which becomes insignificant in the former. For the inconsistent participants, the probability of choosing the safe option is lower (this is so for participants presented with the risk treatment). Older participants presented with the ambiguity treatment are more likely to choose the safe option. Further analysis will be performed in section 3.5.4 (b) to assess if participants in the different groups are less/more risk averse.

Table 3.10: Determinants of choosing safe option

	all	risk	ambiguity
	(7)	(8)	(9)
female	**-0.527****	**-0.674****	**-0.618***
	(0.222)	(0.268)	(0.364)
age	0.035	0.008	**0.068***
	(0.023)	(0.027)	(0.041)
single	-0.187	-0.365	-0.152
	(0.253)	(0.363)	(0.364)
part 1	**-0.159****	-0.011	**-0.445*****
	(0.075)	(0.097)	(0.125)
risk treatment	**-0.630*****		
	(0.206)		
random frame	**-0.433***	-0.410	-0.652
	(0.250)	(0.278)	(0.438)
decreasing frame	**-1.205*****	**-1.267*****	**-1.616*****
	(0.317)	(0.381)	(0.556)
probability	**3.417*****	**2.910*****	**4.533*****
	(0.164)	(0.196)	(0.321)
inconsistent	-0.232	**-0.581*****	0.292
	(0.144)	(0.192)	(0.232)
constant	-0.383	0.116	-1.344
	(0.803)	(1.036)	(1.332)
ln (σ_u^2)	-0.859***	-1.294***	-0.568
	(0.258)	(0.388)	(0.364)

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

3.5.4.(a) Switch point

The data can also be analysed using the ‘switch point’ (Figures 3.6 and 3.7). The switch point is the point at which individuals switch from the risky option to the safe option- (switch from lottery B to lottery A). This will be a scalar with integer values between 0 and 20. The earlier the switch point, the more risk/ambiguity averse the individual. Those switching later are more risk/ambiguity loving. This part of the analysis was carried out for the *consistent* participants only. Using the switch point to assess the behaviour of participants indicates that most students were risk/ ambiguity averse. The percent choosing the safe option in all decisions is higher for those shown the ambiguity treatment than those shown the risk treatment.

In part 2, the number choosing safe option in all decisions increases for both treatments. Around 36% (22%) of those shown the ambiguity (risk) treatment choose to adopt in all decisions and are thus extremely ambiguity (risk) averse in part 1 of the experiment. The proportions in part 1 are almost similar; approximately 21% and 20% for risk and ambiguity respectively. Interestingly, 70% of those who chose the safe option in all decisions in part 1 of the experiment, were presented with order 1 where probability of drought was increasing. Twenty percent were shown order 5 and the rest order 3.

Figure 3.6: Switch point for part1 of the experiment

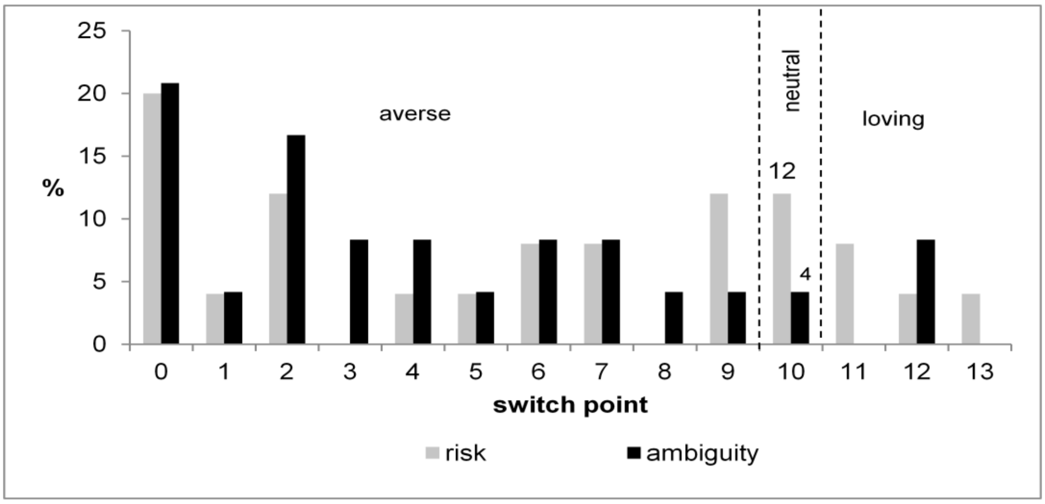
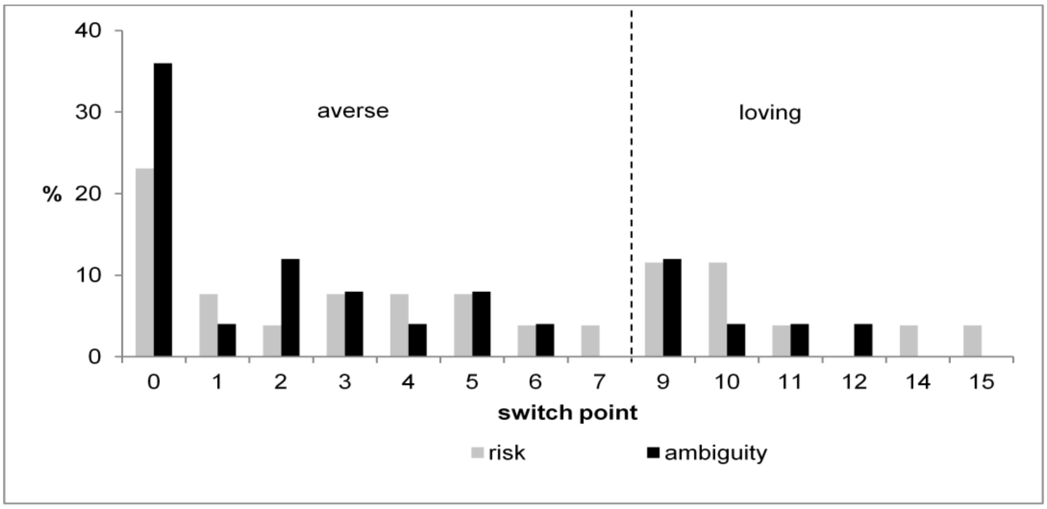


Figure 3.7: Switch point for part 2 of the experiment



When analysed by treatment; for those shown the ambiguity treatment, 80% who chose to adopt at all levels were order 1 participants and in the risk treatment, it was 60% of the participants who were shown order 1 choosing to adopt at all decision levels. One potential weakness of the MPL is that participants are drawn to the centre of the table of decisions and therefore choose the middle row as they go down the rows (Harrison and Rutström 2008), however that is not the case with our results. This can be explained by the way our experiment was framed and our sample of participants who were students at vocational agricultural colleges and thus might have a bias towards adoption of DT varieties. Participants were asked to decide whether or not they would adopt a drought tolerant variety given the probability of drought. We asked how participants chose their decisions; some illustrative responses follow below.

Student 1: 'It is better to obtain low yields than to harvest nothing; that will make matters worse...'

Student 2: 'The possible difference is small and negligible so I go for the drought tolerant variety which certainly assures me of a good yield in any case (drought or otherwise).'

Student 3: '...a farmer should never allow themselves to get zero yield. Even if the cost of the drought tolerant variety is a bit higher, a farmer should never take chances. The experiment however did not specify at what stage the drought is going to happen...'

Student 4: Due to climate change which is somehow unpredictable, it pays off to adopt drought tolerant varieties since you can harvest something either in drought or in rainy conditions. The benefit of adopting a drought tolerant variety outweighs a non tolerant variety.'

In part 1, about 16% are risk loving whilst the percent ambiguity loving is half (around 8%). In part 2, if participants are risk/ambiguity neutral, they are expected to choose the first 8 risky choices and then switch to the safe choice at the decision where, $EV^A = EV^B = 6$. Subjects avoided ambiguity by choosing the safe option since they were guaranteed a payoff. Instead of choosing a payoff of 10, they would be willing to lose 6ECU and 4ECU in the event of a drought or no drought respectively; hence they are paying to avoid the consequences that might be brought about by the ambiguous probability.

3.5.4. (b) CRRA

This part of the analysis includes students who made multiple switches. Interval regressions' using the range of the CRRA allows us to use the inconsistent participants. The CRRA interval is calculated using the point where participants switch from the risky to the safe option. In order to determine the range of the CRRA for the inconsistent participants, the lower bound was determined by the point where the 1st switch was made (lower bound associated with the risky choices made), whilst the upper bound was determined by the last risky choice the student makes (same method used by: Lusk and Coble 2005, Andersen et al. 2006). Andersen et al. (2006) propose that the multiple switching behaviour by students might be due to indifference between the options and one remedy for this would be to ' ... use a "fatter" interval to represent this subject in the data analysis, defined by the first row that the subject switched at, and the last row that the subject switched at. In standard utility theory, this is simply saying that preferences are only required to be weakly convex rather than strictly convex.' As highlighted earlier, decision 20 from both parts was a test to see if the participants understood the experiment. Five[34] participants choose non adoption at these decisions and these were removed from the analysis. The probability of drought was 100%, and participants were expected to adopt the drought tolerant variety as non adoption would result in them receiving a payoff of 0.

Table 3.11 indicates the CRRA at switch point, hence participants who choose 7 risky options then switch to the safe option reveal a CRRA interval between 0.12 and 0.22 for part 1 of the experiment, whilst for part 2, a participant who chooses 10 risky choices and then switches to the safe option, his/her revealed CRRA interval is between -0.79 and -0.56. An interval regression model using a random effects specification was estimated with CRRA interval as the dependent variable. Three models were estimated with; all participants, participants presented with risk treatment and for participants presented with the ambiguous treatment. The results of the maximum likelihood estimates for the interval regression model are presented in Table 3.12.

Table 3.11: CRRA interval at switch point

	CRRA	
Number of safe choices	**Part 1**	**Part 2**
0-1	-2.42	-4.86
2	-1.71	-3.51
3	-1.30	-2.71
4	-1.00	-2.15
5	-0.77	-1.71
6	-0.57	-1.36
7	-0.41	-1.06
8	-0.22	-0.79
9	-0.12	-0.56
10	0.00	-0.36
11	0.12	-0.17
12	0.22	0.00
13	0.33	0.16
14	0.43	0.30
15	0.52	0.44
16	0.62	0.56
17	0.71	0.68
18	0.81	0.79
19 to 20	∞	∞

[34] 4 observations and 1 observation from parts 1 and 2 respectively were dropped because they choose option B in the last decision where the probability of drought was 100%

Table 3.12: Interval regression results

	all	risk	ambiguity
	(10)	(11)	(12)
female	**-0.431***	-0.524	-0.270
	(0.258)	(0.469)	(0.208)
age	0.032	0.037	**0.050****
	(0.027)	(0.050)	(0.023)
single	0.063	0.357	-0.078
	(0.262)	(0.495)	(0.208)
part 1	**0.165*****	**0.321*****	**0.029***
	(0.016)	(0.027)	(0.015)
risk treatment	**-0.400***		
	(0.236)		
constant	-0.339	-0.996	-0.800
	(0.880)	(1.633)	(0.701)
σ_u	0.771***	0.968***	0.477***
	(0.082)	(0.146)	(0.071)
σ_e	0.307***	0.366***	0.202***
	(0.005)	(0.009)	(0.006)
Predicted CRRA	0.248	0.094	0.441
Standard deviation	0.395	0.371	0.351

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

The CRRA coefficient decreases by 0.43 for the female participants, indicating that women in our sample are less risk averse compared to men. This supports the previous results on probability of choosing the safe option. The standard error for this statistic is 0.26. Generally, most studies indicate that women are more risk averse or there are no differences, as highlighted by the summary of studies in (Eckel and Grossman 2008b, Croson and Gneezy 2009), but our results indicate that women in our sample were less risk averse compared to their male counterparts. Evidence from research undertaken by (Moore and Eckel 2003) and Schubert et al. (1999) indicate that women were more willing to take risk, however this was in the 'loss domain' where lotteries are presented as potential losses (framed as insurance). In the former, students are presented with choices between a certain payoff and a lottery using the Becker-Degroot-Marshcak method. In Moore and Eckel (2003) participants were provided with a range of probabilities or range of payoffs. This behaviour of the female participants can be attributed to the fact that most of the female students in our sample were single and younger than their male counterparts. The average age for the women was about 26 years compared to 31 for the men. Around 64% of the participants who were single were women. Single participants maybe risk prone since they do not have any commitment or responsibilities compared to the married. Bouhlel, Mzoughi and Chaieb (2011) and Hartog, Ferrer-i-Carbonell and Jonker (2002) found that single individuals were less risk averse compared to married couples and studies show risk aversion may increase with age (Hartog et al. 2002, Donkers, Melenberg and Van Soest 2001).

In all models, the two parts of the experiment have statistically significant differences in risk attitudes. Part 1 of the experiment has a higher CRRA at the 1% level for all and risk participants. For those shown the risk treatment, the CRRA increases by 0.32 in part 1 of the experiment, whilst it increases by about 0.17 for all participants. We cannot use this result to conclude that participants were more averse in part 1 as the positive significant coefficient is due the higher CRRA intervals for each decision in part 1 compared to 2 (refer to Table 3.11: the CRRA for part 2 for all 20 decisions ranges from -4.86 to ∞ whilst for part 1 the range is from -2.42 to ∞). We therefore need to estimate other models to assess if participants were more averse in part 1 compared to part 2 using the number of safe choices as the dependent variable. Results of these estimations are presented in section 3.5.5.

Model (10) shows that those presented with the risk treatment were less risk averse compared to those shown the ambiguity treatment. The CRRA decreases by 0.4 for those presented with the risk treatment with a standard error of 0.24. For the ambiguity treatment, age is a determinant of CRRA. The older participants have a higher CRRA at the 10% level, indicating that they were more risk averse. Damodaran (2008 pg. 42) reviews literature on risk aversion and concludes that risk aversion increases with age. The age in our sample varies from 19 to 45 years. When we control for order effects, order 1 and 4 have a positive relationship with CRRA for all participants, and if estimated for ambiguity participants only, participants shown the decreasing frame (order 2) were less averse compared to the other orders (CRRA is lower by around 0.45). Results of the estimated models are shown in Appendix 3.5. Models including the order for the separate risk and ambiguity treatment need to be taken with caution as we had small sample sizes in those categories. The graphs of the predicted CRRA for the risk and ambiguity treatments provide evidence that most of the participants were risk averse. Figure 3.8 shows the kernel density of predicted CRRA using the epanichnikov kernel and there are clear differences in the behaviour of participants shown the risk and the ambiguous treatments.

Figure 3.8: Predicted CRRA for the risk and ambiguity treatments

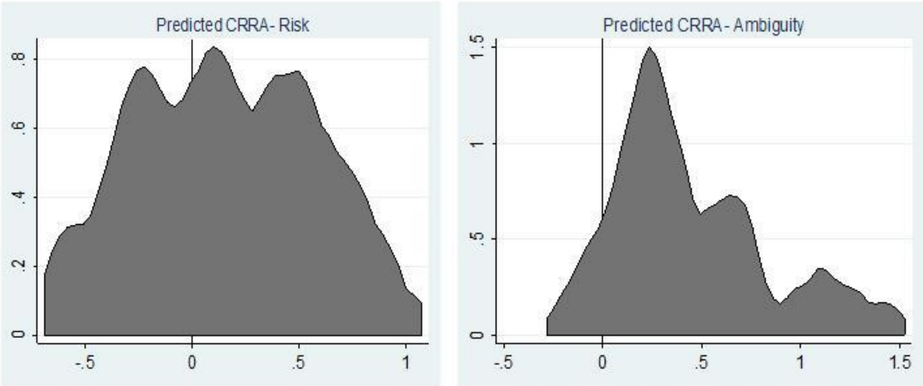
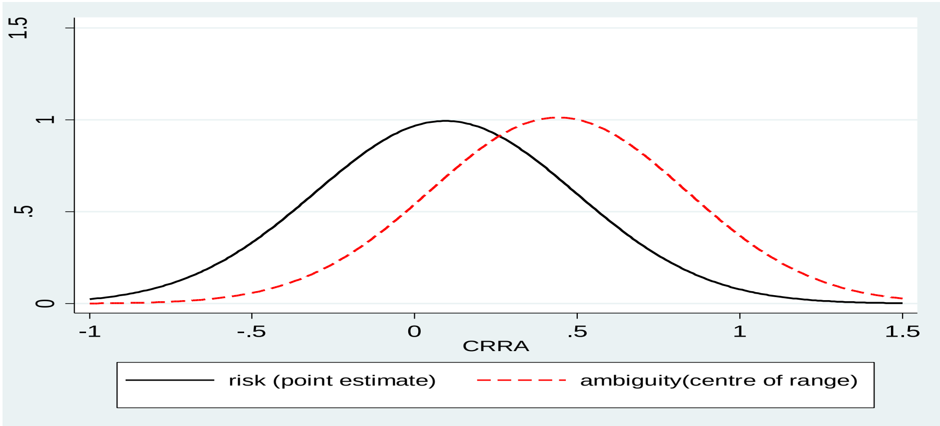


Figure 3.9: Normal distribution curves for the risk and ambiguity treatments



Hence, we can conclude that participants who were shown the ambiguity maybe did not make their decisions based on the centre of the range. Participants who were shown the ambiguity treatment were more risk averse compared to those who were shown the point estimate (Figure 3.9). The graph shows the normal distribution curves estimated from the kernel density function for ease of comparison[35]. From the figure we can conclude that on average, the ambiguous participants acted more like pessimists and made decisions by possibly using probability of drought that was higher than the centre of the range. There was more uncertainty in the range compared to the risk treatment which had a point estimate. As discussed earlier, an inclination towards the lower end of the range indicates optimism, as the probability of drought was lower whilst the opposite indicates pessimism. If pessimistic, participants assume the worst possible scenario. For example, when told that the probability of drought in between 20 and 60%, participants evaluate the lottery using the maximum (pessimistic) or a value higher

[35] Shapiro-Wilk test for normality were done. This tests the hypothesis that the distribution is normal, H_0: Distribution of the residuals is normal. We fail to reject the null for both ambiguity and risk and conclude that the residuals for the predicted CRRA are normally distributed. Z= 7.56, p=0.00 and z= 11.1, p=0.00 for risk and ambiguity respectively.

than the centre of the range. Table 3.13 shows the results of an interval regression assuming participants were behaving as pessimists.

Table 3.13: Interval regressions assuming pessimistic behaviour

	all	**ambiguity**
	(13)	(14)
female	**-0.435***	-0.282
	(0.260)	(0.231)
age	0.034	**0.054****
	(0.026)	(0.025)
single	0.062	-0.086
	(0.264)	(0.229)
risk treatment	-0.269	
	(0.238)	
part 1	**0.189*****	**0.072*****
	(0.016)	(0.016)
constant	-0.537	-1.058
	(0.852)	(0.773)
$\boldsymbol{\sigma_u}$	0.786***	0.517***
	(0.083)	(0.077)
$\boldsymbol{\sigma_e}$	0.312***	0.224***
	(0.005)	(0.007)
Predicted CRRA	0.185	0.488
Standard deviation	0.353	0.557
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1		

Female is a still a significant variable for all participants. The CRRA coefficient decreases by 0.44 for the female participants, indicating that women in our sample were less risk averse compared to the men. Age remains a significant variable for the ambiguity treatment. It has a positive relationship with CRRA assuming participants are pessimists at the 10% level of significance. The CRRA increases by 0.05, thus the older participants are more risk averse compared to the younger ones.

3.5.5. Estimations using number of safe choices as the dependent variable

The determinants of risk/ambiguity aversion can also be assessed using an ordered probit model or linear regression with number of safe choices as the dependent variable. In this section, we will present results from random effects models using linear regression[36] (Table 3.14). Both models show that older participants and those presented with the ambiguity treatment, were more averse compared to the younger and those presented with the risk treatment respectively.

[36] Ordered probit models were also estimated with number of safe choices as the dependent variable. The signs on the coefficients are unchanged and significance levels are almost similar with those in the linear regression models. Order 1 becomes significant (p=0.04; coef=1.48).

Table 3.14: Determinants of risk/ ambiguity aversion (linear regression)

	all	**all**	**all**	**consistent**
Dependent variable: number of safe choices	**(15)**	**(16)**	**(17)**	**(18)**
female	-1.769	-1.769	**-1.909****	**-2.816*****
	(1.101)	(1.102)	(0.892)	(0.916)
age	**0.236*****	**0.236*****	0.125	0.032
	(0.085)	(0.085)	(0.092)	(0.090)
single	0.815	0.815	-0.758	**-1.956****
	(1.034)	(1.035)	(1.155)	(0.980)
risk treatment	**-2.482*****	**-3.210*****	**-2.899*****	**-2.385****
	(0.877)	(1.008)	(0.907)	(1.024)
part 1	-0.566	**-1.308*****	**-1.308*****	**-1.526*****
	(0.495)	(0.485)	(0.485)	(0.492)
risktreatment*part1		1.456	1.456	**2.126****
		(0.961)	(0.962)	(1.074)
order 1			1.299	1.359
			(1.203)	(1.251)
order 2			**-3.136****	**-5.119*****
			(1.495)	(1.344)
order 3			-0.317	0.533
			(1.499)	(1.600)
order 4			1.351	1.493
			(1.332)	(1.523)
constant	10.14***	10.51***	14.46***	18.22***
	(3.076)	(3.062)	(3.072)	(2.824)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

When an interaction term to measure if there is a significant difference between the ambiguous and risky treatment for the parts is included in the model, part 1 becomes a significant variable. This indicates that participants were more risk averse in the second part of the experiment compared to part 1 with the former on average choosing around 1.3 more safe options all things being equal. The interaction term, *risktreatment*part1* is however, not significant.

If we control for order effects, female and order 2 become negatively significant. Participants presented with the decreasing probability of drought frame, are more tolerant compared to those presented with the other orders at the 5% level of significance. These results are consistent with (Lévy-Garboua et al. 2012) who report findings indicating higher risk aversion for the decreasing and random frame compared to the increasing one; they attribute the differences between the increasing and decreasing frame to inconsistencies as the framing variable becomes insignificant for the consistent participants. In our case, if we estimate the model for participants consistent in both parts; the coefficient on order 2 becomes more highly significant, the interaction term becomes significant and so does the variable *single*. The risk seeking behaviour by participants presented with the decreasing order can be attributed to the anchoring biases that were described earlier. As expected, single participants were less risk averse than married.

3.5.6.Risk perception elicitation

Question: Is there any significant relationship between risk perception and risk or ambiguity preference/attitude?

In order to determine the participants' perceptions, we used an instrument which asked them to rate the threat of climate change in different scenarios. Persistent droughts are one of the impacts of climate change in Sub Saharan Africa. When asked the open ended question, '*When you hear or think of climate change what comes to mind?*–More than half of the participants (54%) mentioned 'droughts'. To measure risk perception, participants were asked to rate the threat of climate change on a Likert type scale that ranged from *not a threat* to *a very serious threat*. Participants were also given the option to say they 'didn't know enough to give an opinion'. Responses are presented in Table 3.15. Around 71% of the participants indicated that climate change was a very serious threat to Zimbabwe's agricultural sector and around 56% said it was a very serious threat to the non human nature. None of the students thought climate change was 'not a threat' for their local community, Zimbabwean people and people in other African countries.

Table 3.15: Risk perception on climate change threat (% of participants)

Threat on:	don't know	not a threat	not very serious	somewhat serious	serious	very serious	Mean* (s.d)
you and your family	8.5	3.4	8.5	18.6	39.0	22.0	3.74 (1.04)
your local community	10.0	-	10.0	11.7	31.7	36.7	4.06 (0.10)
Zimbabwean people	3.4	-	13.6	13.6	20.3	49.2	4.09 (1.10)
Zimbabwe's agricultural sector	-	1.7	-	6.7	20.0	71.7	4.60 (0.76)
people in other African countries	8.3	-	5.0	15.0	30.0	41.7	4.18 (0.90)
people in developed countries	1.7	13.3	15.0	10.0	15.0	45.0	3.64 (1.50)
non-human nature	11.9	8.5	3.4	5.1	13.6	57.6	4.23 (1.30)

*Mean does not include responses for 'don't know'; likert scale is from 1 to 5

Our risk perception measure was created by summing up the Likert scale responses for each of the participants. We then standardised the measure (rescaled it to have a mean of zero and standard deviation of 1). To assess if our risk perception measure provides a reliable and valid measure, we used the

Cronbach alpha statistic (Cronbach 1951). The statistic tests the internal reliability/ consistency of a summative rating scale such as the Likert scale. If all items are included in our index, alpha is 0.67. Our alpha is close to the recommended 0.70. In their analysis of risk perception on consuming genetically modified food, Lusk and Coble (2005) summed up the responses from a Likert scale (ranged from 1=strongly disagree to 9=strongly agree) to create a risk perception measure. They asked consumers about their perception of GM food production in relation to themselves, their family and human health in general. Leiserowitz (2006) constructed a risk perception index to demonstrate that public responses to climate change are influenced by both psychological and socio-cultural factors, by combining nine variables on: holistic concern; likelihood measures of worldwide and local impacts of global warming on standards of living, water shortages and disease, the seriousness of global warming for non-human nature and the seriousness of the current impacts of global warming around the world).

To assess if there is a significant relationship between risk attitudes and perception, we included the risk perception measure in the probit model for choosing the safe option and linear regression which were discussed before. Results are shown in Table 3.16. The variable *perception* is not significant in models (19) and (21), but when the interaction term *perception*risktreatment* is included, the former becomes significant for the probit model. The likelihood of choosing the safe option increases for those participants who perceive the threat of climate change to be higher. Climate change impacts are ambiguous and the presence of ambiguity can influence individuals' perceptions regarding this issue. Ambiguity in the probability distribution of for example the likelihood of extreme weather events, means that individuals may not be able to measure the risk involved, and hence are likely to choose the safe option when presented with such a decision. Participants, who perceive climate change to be a threat and were presented with the ambiguity treatment, were more risk averse as indicated by the negative coefficient on the interaction term. When the models for the risk and ambiguity treatments are run separately, *perception* is positively significant for the later but is insignificant for the risk treatment. Since we have already established that participants presented with the ambiguity treatment might probably have been behaving as pessimists, this can also perhaps explain why *perception* is significant for them.

Table 3.16: Risk perception regression results

Model	Probit		OLS	
Dependent variable	Choosing safe option		Number of safe choices	
	(19)	(20)	(21)	(22)
female	-0.251	-0.605*	-0.954	-2.358
	(0.280)	(0.331)	(1.720)	(1.717)
age	0.029	0.034	0.160	0.180
	(0.024)	(0.023)	(0.113)	(0.118)
single	-0.193	-0.213	-0.973	-1.001
	(0.234)	(0.226)	(1.434)	(1.338)
part 1	-0.185**	-0.185**	-0.806	-0.806
	(0.078)	(0.078)	(0.597)	(0.598)
risk treatment	-0.438**	-0.447**	-2.020**	-2.032**
	(0.190)	(0.183)	(0.969)	(0.918)
probability	1.329***	1.329***		
	(0.139)	(0.139)		
perception	-0.001	**0.311***	-0.0270	1.225
	(0.097)	(0.188)	(0.509)	(0.849)
perception*risktreatment		**-0.452***		**-1.842***
		(0.236)		(1.097)
household head	-0.061	-0.351	-0.043	-1.212
	(0.389)	(0.407)	(1.918)	(1.698)
constant	-0.216	-0.092	12.40***	12.77***
	(0.729)	(0.708)	(4.091)	(4.052)
ln (σ_u^2)	-1.483***	-1.575***		
	(0.321)	(0.324)		
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1				

The questionnaire to assess climate change risk perception was administered after our experiment so maybe this influenced the responses, and there might be some correlation between perception and being presented with ambiguous probabilities. Further research can be undertaken to test this effect by administering the questionnaire before the experiment.

3.6. Conclusion

We elicit the risk and ambiguity attitudes of college students in Zimbabwe using experimental methods. Depending on the context of the decision, past experiences and so forth participants are bound to have different attitudes. Results of this study can be used to compare risk and ambiguity attitudes of students in developing countries to the data from multiple studies using students in developed countries. This has important implications for social and economic development as it helps us gain insights into behaviour in the face of risk and uncertainty. No studies were found that exclusively used MPL to measure ambiguity aversion and also measured order effects, so this research provides significant results to that effect.

Our results indicate that in general, students were both risk averse and ambiguity averse. In addition we assess the determinants or characteristics driving them to be generally averse and if there are differences when presented with risk or ambiguity. Risk and ambiguity attitudes measure individual behaviour and as our results show, this depends on the context of the decision, framing, past experiences and so forth. Two groups of participants were used; one group was given risky gambles whilst the other group was presented with ambiguous gambles. The probabilities for the risk treatment were equal to the centre of the range for the ambiguous ones. Those presented with the risk treatment were less risk averse compared with those shown the ambiguity treatment. Participants, who were presented with the ambiguity treatment, behaved as pessimists and perhaps made decisions based on probability of drought that was higher than the centre of the range. Contrary to the comparative ignorance hypothesis which states that ambiguity aversion disappears when participants evaluate risky and ambiguous bets in isolation, our results indicate clear significant differences in the behaviour of participants presented with ambiguity and those presented with risk. We used a between-subject approach to assess the ambiguity and risk attitudes of students. Although we did not employ a separate within-subject design to compare results, we can argue that ambiguity aversion does not disappear in our sample.

We find gender differences in risk attitudes, with female participants less risk averse compared to their male counterparts when all subjects are pooled together. We find no evidence of significant gender differences in attitudes within the two conditions: those presented with risk and those presented with ambiguity. Moore and Eckel (2003) and Schubert et al. (1999) found females less risk averse, however, this was in the loss domain; our experiment was presented in the gain domain. Gender differences in our results can perhaps be attributed to the age and marital status of the women in our sample. The females were on average younger and single whilst the men were older and married. Some studies that have been carried out conclude that risk aversion increases with age (Hartog et al. 2002, Donkers et al. 2001) and that single individuals are less risk averse compared to married couples (Hartog et al. 2002). We also find gender differences in consistency; women in our sample were more likely to be consistent compared to their male counterparts. Older participants were significantly more averse in the ambiguous treatment but not so in the risk treatment.

There are expected differences in the behaviour of students in part 1 and part 2 of the experiment. Part 1 was a series of choices between gambles whereas the second part, choices were between a guaranteed payoff and a gamble. Participants were more averse and more consistent in the latter. On average, most of the participants chose more safe options in part 2 compared to part 1 despite the treatment. Part 2 of the experiment was presented to all participants using an increasing order and the payoff for adoption was the same whether or not a drought occurred (participants would get a payoff of 6 whether or not a drought occurred) and was higher than that in part 1. Although not all payoffs were increased by a similar scale results indicates that a higher guaranteed payoff perhaps encourages consistency and increases risk aversion. Regression results indicate that, order 1 (increasing probability of drought) improves consistency relative to order 2 (decreasing probability of drought) and random order.

The data seems to indicate anchoring effects due to varying the order the probability of drought was presented. The increasing order had the highest anchor, whilst the decreasing one had the lowest. Our results show that anchors can serve as reference points, and how information is framed and order it is presented can potentially influence people's perceptions and in turn their decision making. This analysis can be used by consumer marketing and advertising companies. Analysis was also done to find out if there was any significant correlation between risk perception and risk or ambiguity preference/attitude. Participants who perceived the threat of climate change to be higher were more likely to choose the safe option. Results show that participants presented with the ambiguity treatment chose more safe options if they perceived the threat of climate change to be higher compared to those shown the risk treatment.

Further studies can be performed using the same experiment with students who are not majoring in agriculture, for comparison. This particular sample of participants might be biased in their decision making process, since the experiment was framed in an 'agriculture' context. Our experiment was framed in the gain domain; future studies should also include a loss frame. Framing the decision choices as 'probability of rain' instead of drought might produce different results. The way our experiment was framed maybe driving the results based on peoples experiences related to drought. A control treatment where the safe option is framed in a less 'favourable' way and perhaps using two variants of the same cereal crop can test this effect.

The findings from our study highlight the importance of measuring both ambiguity and risk attitudes as there are clear differences in the behaviour of participants presented with information as risky or ambiguous gambles. Results indicate framing and order effects on consistency and risk/ ambiguity preferences. How information is presented induces different reaction patterns, preferences and consistency levels. Our results thus contribute to the increasing body of knowledge on decision making under risk and uncertainty.

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Appendix 3.1: Experiment Instructions

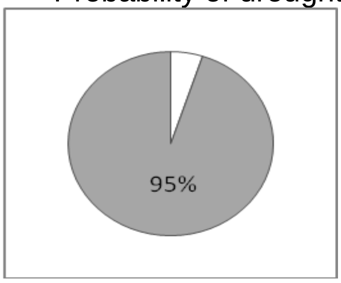
You are about to participate in an economic experiment on crop decision making consisting of **two parts**. The experiment consists of 20 decisions in each part. At the end of the experiment, one round will be randomly selected from each part for payment. Your total earnings which will be paid in **cash** at the end of the experiment will be the average from the two parts. Payoffs are in Experimental Currency Units (ECU), where 1 ECU= $1. Earnings depend on your **individual decisions**. Through your decisions, you might earn a considerable amount of money.

Do not communicate with the other participants. If you have any questions at any time, please raise your hand and someone will come and assist you.

The experiment involves making a series of choices from two options. You are to choose whether or not to adopt a new drought tolerant crop variety. You are told the exact probability that there will be a drought (e.g. 40% probability of drought) OR you are told a range of the probability that a drought will occur (e.g. 20-60% probability of drought). The new crop variety can do well in both rainy and drought conditions.
To help you decide you are given a payoff table, a chart showing the probability that a drought will occur and asked to choose which option you prefer. The payoff table shows that if you adopt the new drought tolerant crop variety and there is a drought, your payoff will be **4** whilst if you do not adopt and there is a drought, your payoff will be **0** (lose everything). Likewise, if you decide to adopt and there is a good rainy season, your payoff will be **6** and if you do not adopt and it rains, your payoff will be **10**.

Decision 1 (Please tick your choice)		Drought	Rain
	Adopt	4	6
	Do not adopt	0	10

Probability of drought



Let's look at Decision 1 for instance, you are told that there is a 95% chance of a drought occurring (which means that there is a 5% chance of a good rainy season); given the payoffs above you have to choose which option you prefer (that is **adopt** the new drought-tolerant variety or **do not adopt** the new drought-tolerant variety).

Appendix 3.2: Mann-Whitney tests on inconsistency

	z	p
order 1 vs. order 2	-0.91	0.361
order 1 vs. order 3	-1.52	0.128
order 1 vs. order 4	-0.69	0.491
order 1 vs. order 5	0.29	0.769
order 2 vs. order 3	-0.58	0.563
order 2 vs. order 4	0.14	0.885
order 2 vs. order 5	1.07	0.284
order 3 vs. order 4	0.67	0.503
order 3 vs. order 5	1.59	0.111
order 4 vs. order 5	0.88	0.380
increasing vs. decreasing	-0.91	0.361
random vs. increasing	0.86	0.389
random vs. decreasing	-0.22	0.827

Appendix 3.3: Average number of safe choices for different groups (all participants)

a) Average number of safe choices within parts

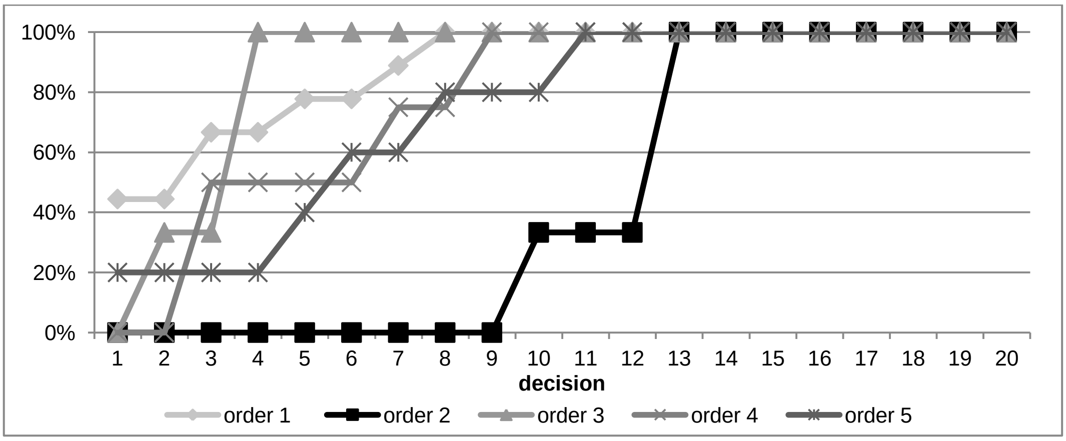
		Part 1			Part 2		
		Mean	**t**	**p**	**Mean**	**t**	**p**
College	Esigodini	14.81	0.510	0.612	15.71	1.000	0.321
	Gwebi	14.27			14.60		
Treatment	Risk	14.13	0.789	0.433	14.00	2.200	**0.032**
	Ambiguity	14.97			16.37		
Sex	Male	14.87	0.602	0.550	16.00	1.5016	0.139
	Female	14.23			14.35		
Marital status	Married	14.42	-0.240	0.811	15.30	0.271	0.787
	Single	14.67			15.00		
Household head	Not head	13.92	-1.752	**0.087**	14.73	-1.138	0.262
	Head	15.80			16.05		

b) Average number of safe choices between parts (part 1 vs. part 2)

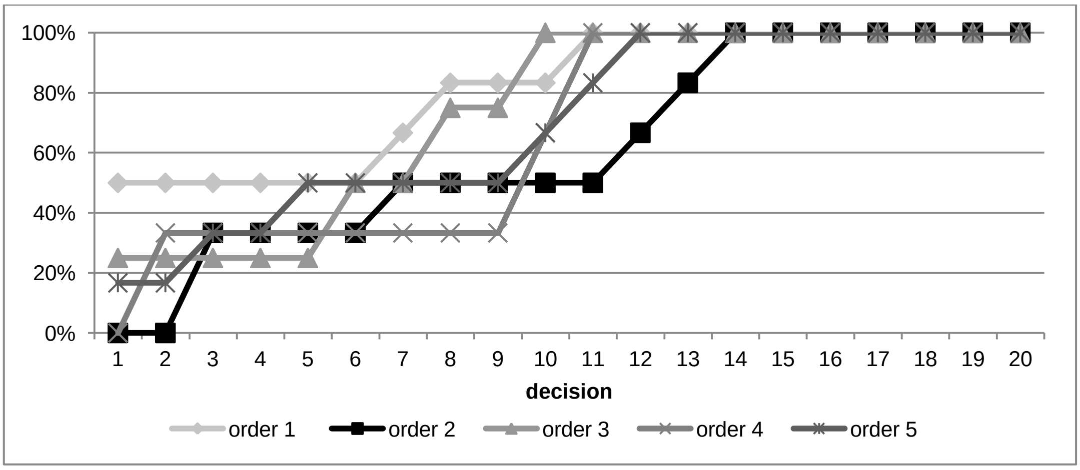
		T- test		**Wilcoxon signed-rank**	
		t	**p**	**Z**	**p**
College	Esigodini	-1.203	0.239	-1.670	**0.095**
	Gwebi	-0.577	0.569	-1.238	0.216
Treatment	Risk	0.178	0.860	-0.476	0.634
	Ambiguity	-2.411	**0.022**	-2.591	**0.009**
Sex	Male	-1.533	0.136	-1.765	**0.076**
	Female	-0.217	0.829	-1.227	0.220
Marital status	Married	-1.229	0.228	-1.765	**0.078**
	Single	-0.532	0.599	-1.224	0.221
Household head	Not head	-1.478	0.147	-2.379	**0.017**
	Head	-0.268	0.791	-0.433	0.665

Appendix 3.4: Proportion choosing safe choice by order and treatment

(a) Ambiguity



(b) Risk

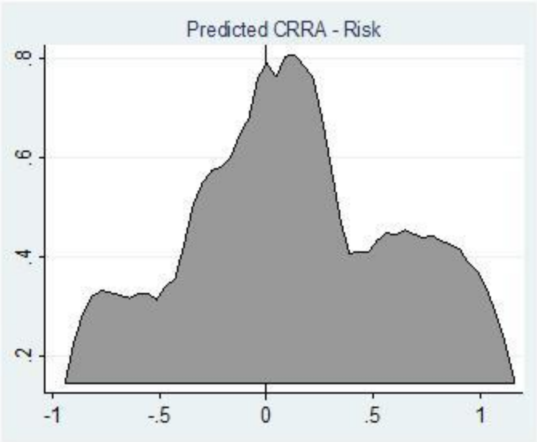


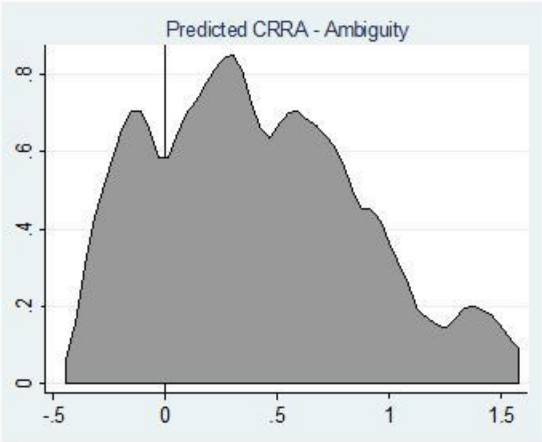
Appendix 3.5: Interval regression controlling for order effects

	all	risk	ambiguity
female	**-0.456****	-0.556	**-0.330***
	(0.222)	(0.432)	(0.185)
age	0.005	0.002	0.030
	(0.023)	(0.045)	(0.019)
single	-0.299	-0.061	-0.193
	(0.250)	(0.572)	(0.180)
part 1	**0.165*****	**0.321*****	**0.028***
	(0.016)	(0.027)	(0.015)
risk treatment	**-0.352***		
	(0.203)		
order 1	**0.706****	0.905	0.391
	(0.303)	(0.554)	(0.248)
order 2	-0.294	0.024	**-0.429***
	(0.307)	(0.614)	(0.252)
order 3	0.297	0.785	0.002
	(0.330)	(0.662)	(0.263)
order 4	**0.579***	0.653	0.384
	(0.340)	(0.668)	(0.271)
constant	0.320	-0.274	-0.255
	(0.760)	(1.622)	(0.610)
σ_u	0.695***	0.898***	0.383***
	(0.074)	(0.136)	(0.057)
σ_e	0.307***	0.366***	0.203***
	(0.005)	(0.009)	(0.006)
Predicted CRRA	0.248	0.122	0.405
Standard deviation	0.501	0.523	0.462

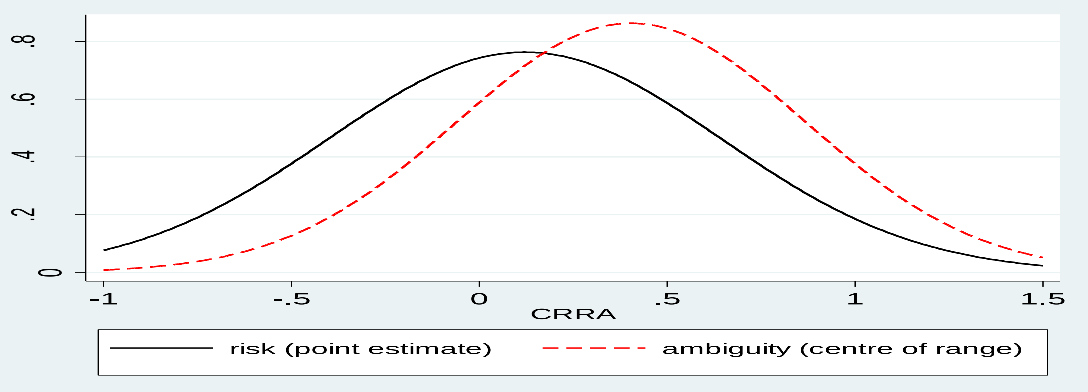
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Kernel densities





Normal distribution curves for the risk and ambiguity treatments



CONCLUSION

This thesis consists of three experimental studies that investigate behaviour when presented with risk and ambiguity. The common subject for the three studies was communication of uncertainty information. Results indicate that the presentation format, context and sample type makes a difference in behaviour.

In the first study, non-specialists who were provided with uncertainty information (90^{th} percentile confidence interval) in a table and bar graph format outperformed those who were presented with just the point forecast. Both the table and graph with uncertainty information were highly significant determinants of choosing the most probable outcome. In some instances however, providing uncertainty information may not have been useful and participants might have interpreted the forecast incorrectly. This indicates the need to constantly test presentation formats and have a two- way communication between providers and recipients in order to improve the communication products. There was a significant decrease in the time participants took to respond to questions as the experiment progressed, possibly indicating a learning effect. This is useful as it indicates that interpretation of a particular presentation format may become easier with familiarity. Participants who were shown the graph with uncertainty information took on average less response time on the ‘more visual’ graph compared to those who were shown the table with uncertainty information, hence the former might have been cognitively easier for participants to interpret and understand. Presenting information in a format that is both visually appealing and takes less time to process the information is useful as it reduces ‘costs’ for users. Providers of risk information such as the Met Office therefore need to invest in developing products that take this into account. The study produced real results that are useful for the Met Office both to help them decide which format to use to best disseminate weather information to the public and to determine the value of presenting probabilistic information-the tested format (bar graph with uncertainty information) is actually currently in use on the Met Office website. Results can help various other sectors that use weather information which include agriculture, aviation, sports, energy, as well as policy makers and the general public. Weather forecast users need information they understand, can interpret and use efficiently to avoid costly decisions in order to make decisions that are as simple as whether or not to carry an umbrella to important decisions like when to fly a plane or what crop to grow and when. Other applications of the study include, pensions giving risk advice, brokers giving investment advice, and government displaying economic forecasts.

In the second and third studies, vocational agricultural students (non-specialists) and smallholder farmers exhibited different behaviour patterns when presented with risk or ambiguity. A modified Holt and Laury (2002) procedure was used to elicit attitudes. Participants were provided with binary decision choices (whether or not they wanted to adopt a drought tolerant variety) with different probabilities of drought where adoption was the safe choice. Subjects in one group were presented with known probabilities whilst another group was presented with ambiguous probabilities (range). For each decision, the centre of the range presented to the ambiguous group was equivalent to the probability under the risk treatment. Results indicate that the context used when presenting risk/ambiguity information has a significant impact on decision making.

Specialists (smallholder farmers) who have had past experiences with drought were extremely risk and ambiguity averse and chose the safe option even at the lowest level of a drought occurring. Although participants presented with ambiguous probabilities chose slightly more safe options compared to those presented with risk; this was not statistically significant (number of safe choices was used as a measure of risk/ambiguity aversion). Female farmers were more averse compared to their male counterparts and significantly chose more safe options. No significant gender differences where found when the aggregate data was analysed using regression analysis. However, gender differences were found for farmers in different geographical locations and there were differences in the factors that affect the ambiguity and risk preferences of male and female farmers when they were analysed separately. Drought tolerant (DT) varieties are examples of technologies that reduce exposure to risk and ambiguity thus investing in DT varieties is a form of insurance against weather or climate change risk. Our results indicate farmers were probably making their decisions based on the *safety first or disaster avoidance principle* in order to avoid starvation. This study highlights a number of issues policy makers should consider. Results indicate heterogeneity and the need to disaggregate samples when analysing research results as there maybe underlying factors affecting different groups. Our study revealed differences in factors affecting risk/ambiguity aversion when the sample is analysed by sex of respondent, marital status and geographical location (district) which are not reflected in the aggregate data. Development planners and policy makers need to target the different priorities each sub group might require. There is need to continue government and private sector initiatives and legislation to ensure women empowerment and more access to productive assets; *total land owned* was a significant determinant for men but not for women. Access to mobile phones and membership to associations had a positive significant impact on farmers' adoption decisions; hence the need to ensure mobile phones are used as information and knowledge platforms for the rural population and associations/farmer groups should be strengthened and supported to encourage more dissemination of agricultural information. Farmers presented with ambiguity indicated they would allocate a greater proportion of their land to the new drought tolerant variety compared to those presented with risk. This information on land allocation can be used by seed companies who produce new varieties. Insurance companies offering weather based insurance can use the results on risk attitudes to model insurance types for the different groups of farmers. The government can use results for social policy, for example regarding insurance subsidies.

Experiments were also conducted with students from vocational agricultural colleges in Zimbabwe who will in the near future be making farming decisions under uncertainty and offering advice to farmers. Results indicate that in general, students are both risk averse and ambiguity averse. Those presented with ambiguous probabilities were more averse compared to those presented with risk. This can be attributed to the greater uncertainty that is present in the former treatment. Participants who were presented with the ambiguity treatment behaved as *pessimists* and perhaps made decisions based on probability of drought that was higher than the provided centre of the range. We found gender differences in risk attitudes. Contrary to general results, female participants in our sample were less risk averse compared to their male participants and this can be attributed to the age and marital status of the former; female participants were on average younger and single. This is however when all subjects are pooled together. No evidence of significant gender differences in attitudes was found within the two groups; those presented with risk and those presented with ambiguity. Results indicate that a higher certain payoff perhaps encourages consistency and increases risk aversion. The increasing frame also increased consistency relative to the random and decreasing probability of drought order. The data seems to indicate anchoring effects due to varying the order the probability of drought was presented. The increasing order had the highest anchor, whilst the decreasing one had the lowest. Our results show that anchors can serve as reference points, and how information is framed and order of presentation can potentially influence people's perceptions and in turn their decision making.

The study provides a baseline on the preferences of future decision makers which can be used for development planning purposes and policy making. There are differences in the behaviour of the experienced farmers (chapter 2) and the future farmers and/or advisers (students). Comparing results can help us gain insight in the development of behaviour in risky and ambiguous situations. The experienced farmers were generally more risk and ambiguity averse compared to the students. Results indicate that policy makers and providers of uncertainty information need to take into account the order and format in which they present information to target recipients. Our results highlight that the way that information is framed and presented is important as in can enhance consistency thus helping in decision making. Increasing the payoff for the safe option resulted in less inconsistency; hence incentives are important-indicating perhaps that individuals perform better when incentivised. There is need to assess both the risk and ambiguity attitudes as clear differences were found in our analyses. Advertising and marketing companies can use the results on anchoring effects when developing consumer products that may require different reference points in order to maximise their rewards. Companies offering insurance advice to this particular group of participants can also use these results.

Farmers and vocational students in the second and third study perhaps used past experiences on droughts as a reference point when they were making their decisions. Most of the specialists (experienced farmers) chose the safe option at all decisions. The results in Chapters 2 and 3 could have been motivated by the way the experiment was framed. Adoption was the safe choice given different probabilities of a drought occurring. Given past experiences of drought in Zimbabwe, participants especially farmers chose to stay safe. Different framing for example using 'probability of rain' might provide different results. This result shows the need to consider the experiential system (source of emotions and instincts in the brain) of information processing that is normally ignored when producing weather or climate change communication products in favour of the analytical one.

Our findings from the three studies produce important results and contribute to the literature on communication of risk and ambiguity, and, decision making under weather and climate change risk.