Loss and Ambiguity Aversion and the Willingness to Pay for Index Insurance
Experimental Evidence from Rural Kenya

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Abstract
This study investigates the impact of ambiguity attitudes and loss aversion on the willingness-to-pay for index insurance among smallholders in Kenya. Basis risk, or the difference between the index and losses actually incurred, is a source of ambiguity in index insurance, and is considered a key barrier to uptake. We gauge and validate incentive-compatible measures of loss aversion, ambiguity aversion and a-insensitivity—the inability to sufficiently discriminate between different levels of ambiguity. Next, we setup a BDM-style framed experiment to measure willingness-to-pay for a standard index insurance product, and a ‘rebate’ index insurance—where the premium payment is made ambiguous, too. Contrary to a previous experiment suggesting higher valuations for the ‘rebate’ insurance, we find no significant difference in WTP for the two designs, on average. Ambiguity-averse participants actually exhibit significantly lower willingness-to-pay in the ‘rebate’ treatment. Finally, we show that low willingness-to-pay is driven across treatments by a-insensitivity. This finding has strong policy implications: if a-insensitive people indistinguishably over-weighting (low) probabilities of basis risk, the latter will be a hindrance to index insurance uptake no matter how low its probability, as long as any ambiguity persists. Our findings are in line with Prospect Theory and contribute to understanding how the workings of index insurance are perceived, underlining the need to experiment with alternative insurance designs that take into account ambiguity attitudes.

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1. Introduction

Index insurance is considered a promising risk-coping strategy for households in developing countries. Recent studies find a positive effect of insurance on technology adoption (Hill & Viceisza, 2012), employment of riskier and higher yielding inputs (de Nicola & Hill, 2013) such as fertilizer, seeds and land. Cai (2016) finds higher investments among insured farmers as well as higher consumptions. Janzen and Carter (2013) find a negative correlation between index insurance and distress livestock sales in Kenya. Index insurance’s pay-out is based on indices such as satellite images or weather stations measuring rainfall or normalized vegetation growth. This overcomes the high transaction costs and information asymmetry problems that constitute barriers for the market of traditional insurance in developing countries. In theory, this could greatly improve access to insurance for the poor and enable them to smoothen income, stimulate investments, increase their revenues and escape potential poverty traps. Unfortunately, uptake of index-insurance, has been rather low (Cole et al., 2013).

Paradoxically, index insurance is particularly undemanded by the risk averse (Falco et al., 2016). The literature on microinsurance attributes the low uptake to financial illiteracy, trust, poor marketing, credit/liquidity constraints and price. Another reason is basis risk, which can be defined as the imperfect correlation between the indemnity payments and the actual losses of the farmer. Indices that measure rainfall for example, are not always accurate for every farmer. Therefore, an insured farmer that experiences a drought, is not paid out if the index measured enough rain in his region. The probability of this happening is unknown to the farmer which constitutes a situation of ambiguity. Ambiguity is different from risk, for which the probability is objective. Both are considered sources of uncertainty. In general economic agents are ambiguity averse, meaning that people prefer to bet on an option with known probabilities than on an option with unknown probabilities (Attanasi et al., 2014). It is seen as a fixed trait of character and can also be interpreted as pessimism (Wakker, 2010). Falco et al. (2016) find that in ambiguous situations people rely on heuristic tools to make investment decisions, such as past experiences or experiences of friends and family. Moreover, index-insurance constitutes a double or compound lottery of either a good or bad harvest and of the index being valid or invalid. Elabed and Carter (2015) show that 66% of cotton farmers in Mali are compound-risk averse, which is strongly correlated to ambiguity aversion (Halevy, 2007), cutting down demand for index insurance in half relative to expected utility theory.

In studies on index-insurance and ambiguity, the focus has been solely on ambiguity aversion. The literature on decision making and ambiguity, however, shows a more diverse pattern of responses to ambiguous situations. Some people tend to be more pessimistic, others are more optimistic. Various studies have found that this response to ambiguity is dependent on whether it is gain or a loss and on the degree of likelihood of the ambiguous event (Baillon & Bleichrodt, 2015; Abdellaoui, 2011; Dimmock et al., 2015). They also observe a second important part of ambiguity, called ambiguity generated
insensitivity or a-insensitivity, which is defined as the inability to sufficiently discriminate between different levels of ambiguity, transforming likelihoods towards fifty-fifty (Wakker, 2010). This is the first study that analyses the full variety of ambiguity attitudes in relation to index insurance. Moreover, to our knowledge this study is the first of its kind that measures ambiguity attitudes of a sample of subsistence farmers in Africa. To this end, we adapted and simplified the methodology of Dimmock et al. (2015) and investigated whether the same results are obtained as found on a Western population. Finally, this study explores which type of ambiguity attitudes have an impact on willingness-to-pay (hereafter WTP) for index insurance with basis risk and whether a different frame of insurance could lead to higher WTP. We tested this by offering half the sample a traditional index insurance and the other half a rebate type insurance, where the payment of the premium only occurs in good years. In bad years the premium is deducted from the pay-out for the rebate type. They are actuarially equivalent, but differ in framing of the insurance. Serfilippi et al. (2016) do a similar WTP-experiment and find that subjects who overvalue certainty, have a significantly higher WTP for the rebate type of insurance, as the certain loss of paying the premium has changed from being a certain loss, to a merely probable loss.\footnote{A shortcoming of their experiment is that it did not include basis risk.} This, they claim may increase the valuation of the insurance, especially for the loss-averse.

Our experiment took place in Meru County, Kenya in May 2017. In total 276 female subsistence farmers, from 13 different farmer groups, took part in our study. They participated in three separate games eliciting their ambiguity attitudes for gains and losses, loss aversion and WTP for two types of index insurance. By combining the results of the three games, we analyse which behavioural components and which type of agents are affected more by a specific type of insurance. Our research shows that ambiguity plays an important role in index insurance design. We confirm the same pattern of ambiguity attitudes as found in the literature and find that it is dependent on the likelihood of the event and on whether it constitutes a gain or loss. In rural Kenya, the average farmer is ambiguity averse to moderate and highly likely gains and to unlikely losses. They are ambiguity seeking for unlikely gains and moderate and highly likely losses. We find a higher estimate of a-insensitivity than in other lab experiments. The inability to sufficiently discriminate between situations with ambiguity, 90% of our sample falls into this category, significantly reduces WTP for index insurance. We also show that farmers are significantly loss averse. Surprisingly we did not find any significant differences between the two insurance designs. Rather, we found that ambiguity-averse people have a significantly lower WTP for the rebate treatment, compared to the WTP for the traditional insurance.

Our paper is structured in the following manner. Firstly, we provide an overview of the existing literature on decision making under uncertainty. Secondly, we sketch the context of our research and experimental design. We then present the results of the games, which we then use for our analysis. Finally we discuss some of the shortcomings of our study before we come to our conclusions.
2. Literature Review and Theoretical Framework

In this section we look into the main literature on decision making under uncertainty. We start with an overview of the history of theories on decision making and how they have tried to explain decision making for ambiguous situations. We then review the main literature on ambiguity attitudes and recent studies on the variety of behaviour found as a response to ambiguous situations. Emphasis is given to Prospect Theory, which seems to be a good model for explaining the variety and complexity of decision making under ambiguity. Core tenets of prospect theory, such as loss aversion and reference-dependence, play an important role in insurance purchasing decisions. This framing aspect of insurance, and the psychology behind it, is analysed further by distinguishing between a traditional index-insurance and a novel type of insurance where the payment of the premium is made uncertain. We finish this section by listing and explaining the hypotheses of this research. A list with definitions with important concepts can be found in Appendix B.

2.1: A history of uncertainty and ambiguity in decision science

In most economic decisions agents face uncertainties, without any available probabilities. Prominent economists such as Keynes and Knight already recognised the importance of uncertainty in decision making at the start of the twentieth century. Knight (1921) distinguished between measurable uncertainty and unmeasurable uncertainty, where the former has knowable probabilities and the latter not. For the remainder of this research, if we refer to risk we mean uncertainty with known objective probabilities. If we refer to ambiguity, we mean uncertainty with unknown probabilities. This distinction is commonplace in the literature on ambiguity. Ambiguity and risk are both a form of uncertainty. Notwithstanding these early insights, for the main part of the 20th century, decision theorists focussed on modelling decision for risk.

A first remedy to unknowable probabilities was provided by the assumption that individuals assign probabilities to unmeasurable uncertainty as degrees of belief. This reduces all uncertainties, for a ‘rational’ man, to risk (Ramsey, 1931). This was axiomatised by Savage (1954) into a theory of choice called Subjective Expected Utility (SEU). A great advantage of this approach is that subjective degrees of belief can be made observable and quantified through choice behaviour (Wakker, 2008). SEU assumes fully rational actors that assign objective probabilities to all uncertain situations. To this day, it is a dominant theory in economics and decision theory as it explains how (rational) people should behave. In some situations this is realistic, due to experience or education one might have in the topic at hand. However, multiple authors have come up with examples of how subjects systematically violate the assumptions of SEU. The first examples and the most well-known are the paradoxes of Allais and Ellsberg. In 1953 Allais showed that subjects show behaviour inconsistent with EU whenever there is an option of certainty. This option of complete certainty, is overvalued relative to options that are probable. Faced with the choice between A: receiving €1000,- for certain or B: receiving €3000,- with

\[2\] In the remainder we will use Subjective Expected Utility (SEU) and Expected Utility (EU) interchangeably.
50% chance of winning, many people would choose option A. Faced with another choice between A: receiving €1000, with 10% chance of winning or B: receiving €3000, with 5% chance of winning, many people would choose option B. This is inconsistent with EU, as the probability ratio between A and B doesn’t change and rational agents should therefore not change their preference. Also note that the expected value of B is larger in both bets. However, in the first situation, A is a certain gain, which is overvalued. In the second situation, the chance of winning is very low, so many people decide to take a gamble. The paradox is known as the common-ratio effect or as the certainty effect.

Another important refutation of EU was given by Ellsberg (1961). We will explain his original experiment in more detail than Allais’ paradox, because the set-up resembles the experimental set-up employed in this study to elicit ambiguity attitudes. Ellsberg demonstrates that most people systematically violate EU when faced with a choice between a risky and ambiguous option. Subjects are presented 2 urns with 100 balls of 2 colours. In urn 1 the ratio of the balls is unknown, they can be either red or black. In urn 2 there are exactly 50 red and 50 black balls. The respondents are told that they have to bet on an urn and if the right colour is drawn, they earn $100. They are asked whether they prefer to bet on a red ball to be drawn from urn 1 or urn 2, followed by the same question for the black colour. The majority of people prefer both the red and the black ball to be drawn from the urn with the known ratio (urn 2). This amounts to the following inconsistency: a preference of Red2 to Red1 and Black2 to Black1 means that you regard Red2 as more probable than Red1. It is inconsistent, however to regard Red2 as more probable than Red1 and simultaneously regard Not-red2 as more probable than Not-red1. This is a clear violation of some of the Savage axioms. (Ellsberg, 1961, p. 651). Even many of Ellsberg colleagues and peers, to their own surprise, followed this inconsistent reasoning, which cannot be reconciled with EU. Ellsberg therefore argues for a category of uncertainty wholly different from risk, which he called ambiguity.

“Ellsberg demonstrates that for unknown probabilities, people behave in ways that cannot be reconciled with any assignment of subjective probabilities at all” (Wakker, 2008). Moreover, EU cannot explain why some people react so strongly to ambiguous situations and others do not. Besides the violations of EU as indicated by the Allais and Ellsberg paradoxes, there is overwhelming evidence against EU, as reviewed by al-Nowaihi and Dhami (2010). This has led to the development of non-expected utility models that in one way or another accommodate the Allais and Ellsberg paradoxes. Most can be either derived from Rank Dependent Utility (RDU) or from the multiple priors model. Rank dependent Utility (RDU) was developed by Quiggin (1982) to accommodate for the Allais paradox and to explain, a puzzle hitherto unexplained by expected utility theory, how the same people can buy lottery tickets and

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3 In a first set of questions the respondent are asked to choose the colour to bet on for both urns. Most respondents state that they are indifferent about the colour.

4 Examples are the failure of the independence axiom, implausible attitudes to risk for small and large stakes, preference reversals, loss aversion, reference dependence and non-linear probability weighting (as reviewed by al-Nowaihi and Dhami, 2010).
purchase insurance. Standard economic theory predicts a concave utility function due to risk aversion. An agent is risk averse if he/she “prefers a deterministic outcome equal to the expectation of a risky outcome over that risky outcome” (Palgrave Dictionary of Economics, 2008). Uniform risk aversion has difficulty explaining why one single person can exhibit multiple risk-attitudes by sometimes gambling (risk-seeking preferences) and also buying insurance (risk-averse preferences). Employing a probability weighting function, RDU allows for the overweighting of only extremely unlikely outcomes such as winning a lottery and needing health insurance. These insights were incorporated into the (Cumulative) Prospect Theory of Kahneman and Tversky, which will be explained in detail in the next section.

Multiple prior models assume that decision-makers, due to having too little information about the true probability distribution, consider multiple possible probability distributions (Gilboa & Schmeidler, 1989). Examples of such distributions are the worst expected utility (MaxMin model), the highest expected utility (MaxMax model) or some weighted average of both extremes (α-MaxMin model5) (Dimmock, 2015, p2). Multiple prior models are especially appealing for theoretical studies, as they still assume Expected Utility theory under risk (Baillon et al., 2016), but non-expected utility under ambiguity. This allows them to make claims on how people should behave. However, likelihood insensitivity has also been commonly found for risk, leading to the inverse-S probability weighting function (Tversky & Kahneman, 1992; Baillon et al., 2016; Fehr-Duda & Epper, 2012). We therefore expect that, considering the descriptive purpose of our study, the multiple prior models are too stylised to adequately explain our results.

SEU and all non-expected utility models use matching probabilities to measure beliefs about the probability of an event occurring. “A probability p is a matching probability of an event E, if a decision maker is indifferent between receiving €x if E occurs and €x with probability p” (Baillon and Bleichrodt, 2015, p 77). For the area of ambiguity, the matching probability (m) is thus the objective probability for which a subject is indifferent between the risky option and the ambiguous option. Probabilistic sophistication is considered a normative requirement of decision models, necessary to use matching probabilities as measures of belief (Machina & Schmeidler, 1995). For probabilistic sophistication to hold and thus for matching probabilities to measure beliefs, they must be additive (p(E) + p(Not-E)=1), independent of the sign of the outcome used to elicit them and the same for gains and losses (Baillon & Bleichrodt, 2015). In their seminal paper “Testing Ambiguity Models through the Measurement of Probabilities for Gains and Losses” Baillon and Bleichrodt (2015) use this method to test the descriptive validity of the main ambiguity models. Their experiments show that subjects violated probabilistic sophistication. Matching probabilities differ for gains and losses, additivity did not hold and violations of additivity differed for gains and losses. Unlikely events were overweighted and likely events were underweighted. They conclude that models that accommodate those violations of probabilistic

5 In this model α reflects the attitude towards ambiguity, or pessimism and optimism.
sophistication best is Prospect Theory, which allows for non-additivity and sign-dependent violations (Baillon and Bleichrodt, 2015). Similarly, Abdellaoui et al. (2011) argue for the development of flexible and rich tools to analyse ambiguity. In this sense models that capture ambiguity by only one parameter of ambiguity aversion are insufficient.

2.2: Ambiguity Attitudes: ambiguity aversion and a-insensitivity
The literature on ambiguity distinguishes between ambiguity aversion and ambiguity generated insensitivity or a-insensitivity. Ambiguity aversion can be described as the preference of betting on known odds over unknown odds. It differs per individual and is related to concepts like pessimism and optimism. It is characterised as a fixed trait of character or the motivational response to ambiguity (Wakker, 2010). A-insensitivity is the cognitive aspect of ambiguity and is also interpreted as the perceived level of ambiguity. The higher a-insensitivity is, the less the subject can discriminate between different likelihoods (Baillon et al. 2016), blurring matching probabilities towards fifty-fifty. This also implies insensitivity to changes in likelihood. There is large heterogeneity in both domains. Empirical studies also find ambiguity-seeking and a-oversensitive behaviour which is the opposite of aversion and a-insensitivity. Neutrality in both the motivational and cognitive component is also found and implies rational behaviour in the sense of Expected Utility theory. Together these responses to ambiguity constitute the ambiguity attitudes.

Abdellaoui (2011), Baillon et al. (2015, 2016) and Dimmock et al. (2015) find evidence that ambiguity aversion is dependent on the likelihood of the event. They find that most people are ambiguity-seeking for low likelihoods and ambiguity averse for high likelihoods, resembling the pattern found for risk attitudes. Subjects tend to underweight highly likely and overweight highly unlikely events, resulting in an inverse S-shaped weighting function for ambiguity. This is theoretically parallel to the concept of likelihood insensitivity for probability weighting under risk as found by Tversky and Kahneman (1992). Various authors have found that subjects are more insensitive to likelihoods for uncertainty than for risk (Kahneman & Tversky, 1979; Kahn & Sarin, 1988; Kilka & Weber, 2001; Abdellaoui et al., 2005; Wakker, 2010, as cited by Baillon et al., 2016). Most studies assume that a-insensitivity for gains and losses are the same, or did not measure ambiguity aversion for losses with varying likelihoods. Baillon and Bleichrodt (2015) find that a-insensitivity is larger for losses than it is for gains, but they do not provide an estimate of this in their paper.

Whereas ambiguity aversion, is considered an immutable (at least on the short term) character trait, a-insensitivity is seen as a cognitive bias that could be reduced. Baillon and Bleichrodt (2013) give proof of this relation by showing that a-insensitivity was reduced with new information, while ambiguity aversion was largely unaffected. Li (2016) finds that agents who are more a-insensitive are less able to cope with ambiguous situations and are prone to make sub-optimal decisions. Abdellaoui et al. (2011) show that subjects are more insensitive to changes in likelihood for less familiar sources of uncertainty,
which is in line with this learning effect. It is important to note that this implies that the source of uncertainty plays a crucial role in measuring ambiguity attitudes.

An overview of ambiguity attitudes found for a representative sample of the U.S. population (N=2991) is given by Dimmock et al. (2015). Their results will serve as a benchmark for our study as our elicitation method of ambiguity attitudes is largely based on their study. They find using an Ellsberg-like survey module, that roughly 52% is ambiguity averse, 10% ambiguity neutral and 38% ambiguity seeking. Ambiguity neutrality implies no deviation from Expected Utility theory. This means that ten percent of the U.S. population behaved as a fully ‘rational’ agent. They also find a reflection effect, meaning that ambiguity attitudes for losses are a mirror image of the attitudes for gains (Dimmock et al., 2015). Baillon et al. (2016) show that for models that use decision weights, like prospect theory, ambiguity attitudes reflect pessimism and likelihood insensitivity as well as it assumes non-expected utility for risk. A-insensitivity extends likelihood insensitivity to the realm of ambiguity.

Considering the fact that in this study we are interested in insurance decisions of Kenyan farmers, we will take recourse to the model that is able to explain all patterns of decision making under uncertainty. Wakker (2014, p.14) concludes that: “Prospect Theory is the most popular theory for predicting decisions under risk today. [...] It also outperforms other theories for predicting decisions under ambiguity.” Baillon and Bleichrodt (2015) and Abdellaoui (2011; 2016), also suggest that PT is indeed an appropriate model for decision making with ambiguity. We therefore assume non-expected utility throughout, excluding a priori multiple prior models as they assume expected utility for risk. We will therefore devote the next sections to Prospect Theory and its key assumptions.

2.3 Prospect Theory
Prospect Theory was first developed in 1979 by Israeli psychologists Kahneman and Tversky in their seminal work “Prospect Theory: an Analysis of Decision under Risk”. It proposes an alternative to rational choice or expected utility theory (Tversky & Kahneman, 1992). Kahneman and Tversky give an overview of examples how people systematically violate predictions of expected utility theory. They claim that EU cannot explain how framing can change the decision of the individual or why people exhibit risk-seeking behaviour in some situations and risk-averse behaviour in others (Edwards, 1996, p. 19). Using a variation of the Allais-paradox, Kahneman and Tversky argue that individuals underweight probable outcomes relative to outcomes that are certain (Kahneman & Tversky, 1979, p. 265). This certainty effect explains risk-aversion for gains and risk-seeking for losses. Another effect, called the isolation effect, prescribes that when choosing between two prospects, common characteristics are ignored, isolating the differences between the two prospects. Because a decomposition of various prospects into similarities and differences can be done in various ways, the framing will influence decision making (Kahneman & Tversky, 1979, p. 271). Marketing is a good example of how framing and the isolation effect can induce individuals to deviate from expected utility theory. Thirdly, the reflection effect states that choices among losing prospects are a mirror image of choices among gain
prospects (Kahneman & Tversky, 1979, p. 268). In 1992 Kahneman and Tversky published a modified version called Cumulative Prospect Theory, incorporating the insights of Quiggin on the importance of probability weighting of Rank Dependent Utility, to address limitations of the original. For this study we consider this modified version, while referring to it as Prospect Theory (or PT).

“Prospect Theory is still widely viewed as the best available description of how people evaluate risk in experimental settings.” (Barberis, 2013, p. 173). Outside the laboratory, many theoretical models still assume EU, explaining how rational individuals should behave. In the last decade more researchers have tried to encompass prospect theory in economic settings, especially in the field of behavioural economics. Prospect theory allows for violations from expected utility by 4 concepts. It introduces reference dependence, which implies that people derive utility from gains and losses relative to some reference point. Rather than absolute levels of wealth, utility is derived from a (subjective) status quo. Secondly, the theory assumes loss aversion, i.e. the idea that people are more sensitive to a loss than to a gain of the same magnitude. This results in a steeper value function in the loss domain than in the gain domain. The third concept is diminishing sensitivity, meaning that replacing a €100.- gain (loss) to €200.- gain (loss) has a higher utility impact than replacing a €1000.- gain (loss) with a €1100.- gain (loss), resulting in a value function that is concave for gains and convex for losses. This can explain risk-aversion for gains of moderate probability and risk-seeking behaviour for losses. Lastly, prospect theory assumes that subjects use decision weights rather than the objective probabilities to weight the outcomes. Subjects tend to overweight the probability of extremely unlikely outcomes and underweight the probability of highly likely outcomes. Prospect theory is not based on final wealth and probabilities, but rather on values assigned to gains and losses with respect to a reference point and decision weights (Kahneman, & Tversky, 1979, p. 277). The value function refers to the subjective value of the outcome, which includes concepts like loss aversion and diminishing sensitivity. The weighting function transforms the objective probabilities into subjective probabilities using decision weights.

Barberis (2013) suggests that prospect theory can provide important explanations for insurance markets where risk plays a crucial role. Throughout the literature on insurance, concave utility due to expected utility and risk aversion is assumed (Wakker, 2008). As indicated before, empirically, a more complex pattern has been found with risk aversion for moderate and high likelihood of gains and for low likelihoods of losses, but with risk seeking for gains with low likelihood and for losses with moderate or high likelihoods (Ibid). PT’s value function alone cannot explain why people gamble or why people buy insurance. If people are generally risk-seeking for losses and risk-averse for gains, then gambling and insurance should not have many customers. Decision weights, leading to overweighting of unlikely and underweighting of likely probabilities, solves this problem.

Barberis (2013) gives an overview of the literature of Prospect Theory applied to insurance markets and how reference-dependence plays a role in framing insurance. Sydnor (2010) explains why individuals
opt for a higher monthly premium, with a lower deductible even though the probability of filing a claim is very low. Most people prefer to pay $100 a month more in premium than pay an additional $500 in deductible more when filing a claim. Sydnor states that subjects overweight the probability of filing a claim resulting in this violation of EU. It also depends on the reference point taken. Köszegi and Rabin (2007) argue that the reference point is the expectation about future outcomes, with the premium as an expected monthly expense. The deductible then only arises in the event of a claim. Loss aversion is higher for this unexpected deductible than for the expected premium. Therefore it is willing to pay a higher premium. Du, Feng and Hennessy (2014) find that farmers in the United States of America do not optimise their crop insurance coverage according to EU theory. Bougherara and Piet (2014) and Bocquého, Jacquet and Reynaud (2014) use show that farmers’ decisions are better modelled using PT (as cited by Babcock, 2015). The reference point taken to evaluate gains and losses is pivotal in explaining insurance decisions. According to Eckles and Wise (2011) the reference point taken alters the value of insurance and the level of coverage chosen. Brown (2008) argues that farmers do not take the reference point of expected wealth after the insured event is realised, but rather see insurance as a stand-alone investment. The value of insurance is then judged based on gains and losses in isolation from the effects of insurance on overall income or consumption. Farmers thus frame insurance as a simple lottery rather than a risk management tool. “A loss occurs when the premium paid is greater than the indemnity. A gain occurs when the indemnity exceeds the premium paid.” (Babcock, 2015, p.1372).

Babcock tests how three different reference points explain the coverage level observed in American crop-insurance decisions. The first reference point is initial wealth. According to Sydnor (2010) this would lead to immediate losses when the premium is paid. Reynaud (2014) suggests that this may explain low crop insurance in Europe. A second reference point is expected future wealth. As time passes, the insurance premium is considered as sunk costs and are not included in the calculation of expected wealth and thus of the reference point. A third reference point equals the costs of the premium, framing insurance as a simple lottery. Babcock (2015) finds that this latter reference point comes closest to explaining empirical crop insurance coverage decisions among American farmers. Framing effects, the reference point taken, loss aversion and probability weighting are thus subjective but important determinants for explaining insurance uptake. They might also play an important role for crop-insurance uptake among subsistence farmers in Kenya. We now consider a final alternative to non-expected utility provided by Andreoni and Sprenger.

2.4: Insurance contract design
“Intertemporal decision-making involves a combination of certainty and uncertainty. The present is known while the future is inherently risky.”(Andreoni & Sprenger, 2012, p. 3373). This is essentially the reason why insurance exists. Andreoni and Sprenger follow the intuition of the certainty-effect of the Allais paradox, to validate EU rather than refute it. As Andreoni and Sprenger indicate in their paper, Allais already argued the same intuition in his 1953 paper Allais (1953, p. 530), that individuals act as
utility maximisers when 2 options are far from certainty, but when one option is certain and the other uncertain, then a disproportionate preference for certainty prevails. Rather than throwing EU out with the bathwater, Andreoni and Sprenger state that EU is only violated when certainty is present. When it’s not present, subjects do follow the predictions of EU. They claim that this cannot be explained by prospect theory or any other non-expected utility theories (Andreoni & Sprenger, 2012, p. 3358). Unsurprisingly, subjects strongly prefer certainty when its available. Most interestingly, they find that when certainty is not present, so when there is no 100% payment option, subjects’ behaviour closely mirrors the predictions of EU (Andreoni & Sprenger, 2012, p. 3359). They argue that Prospect Theory’s probability weighting cannot account simultaneously for the disproportionate preference of certainty when present with EU when far away from certainty.

The notion that people behave differently when there is a choice between a fully certain and an uncertain option than if there are only uncertain options, deserves more attention. This could have implications for insurance design as well, which we will examine in our experiments. This line of thinking has been developed by Serfilippi et al. (2016) who test whether people that greatly value certainty undervalue the benefits of insurance contracts. They test this this in a behavioural experiment with farmers in Burkina Faso. Using choice lists with risky and degenerate lotteries, i.e. lotteries with a probability of 1, they come up with a measure of Discontinuous Preferences of Certainty (DPC). When subjects exhibit DPC, they overvalue the utility of a certain choice (or degenerate lottery in PT) relative to uncertain choices. In this setting, the premium payment of insurance policies is seen as a certain loss. It is hypothesised that this certain loss is overvalued by DPC agents, claiming that if there are only uncertain options, there would be less deviations from expected utility theory. They find that 30 percent of the farmers exhibit DPC. Next, they offer all farmers two different designs of insurance contracts: a traditional insurance and one with a premium rebate in bad years. The subjects have to indicate their WTP for both contracts. WTP for the DPC farmers rose 30 percent for the rebate insurance, in contrast to no significant change in WTP for the non-DPC subjects. The rationale is that the traditional insurance contract offers an option of certainty, i.e. paying the premium in all states of the world, which is (negatively) overvalued by the DPC-subjects. In contrast, in the rebate insurance design the certain loss is now a probable loss, making it not fully certain. The argument is that without the certainty effect, subjects behave according to EU. This affects those subjects who were relatively more sensitive to the certainty effect and now that the certain loss of paying a premium is gone, exhibit significantly higher WTP for insurance. A shortcoming of this research is that it does not incorporate basis risk in the experimental design, which is arguable the most important source of uncertainty in index-insurances.

2.5 Synthesis and Hypotheses
The literature review has shown that Prospect Theory is a promising theory of choice for our study as it can explain the heterogeneity of behaviour towards risk and ambiguity. Probability weighting, loss aversion, reference dependence, reflection and ambiguity attitudes all seem to play an important role in
explaining insurance purchasing decisions. Combining the literature on ambiguity attitudes and prospect theory led us to construct the first three hypotheses 1-3. We subsequently provide a synthesis of ambiguity, prospect theory and insurance design which resulted in hypotheses 4-6.

Our first hypothesis (1) is that ambiguity attitudes of Kenyan farmers will differ for gains and losses and that the average farmer will be ambiguity averse for likely gains and unlikely losses and ambiguity seeking for unlikely gains and likely losses. This is the pattern of ambiguity attitudes found in the literature and we expect to find it as well in our sample. Our second hypothesis (2) is that a-insensitivity will be higher for our sample than for samples from similar studies in Western countries. A-insensitivity is the cognitive part and can be reduced through learning and experience. We expect that the fact that our population has enjoyed less education and experience of probabilistic concepts results in a higher estimate of a-insensitivity. Our third hypothesis (3) is that we expect Kenyan subsistence farmers to be significantly loss averse. This means that they are more sensitive to a loss than to a gain of the same magnitude.

For the elicitation of WTP for index insurance we follow the distinction in design made between a traditional type of insurance and a rebate type of insurance. For the traditional type the payment of the premium is certain in all states of the world and for the rebate-type of insurance subjects only pay the premium if the harvest is good. In contrast to the design of Serfilippi et al (2016), we include basis risk as an extra source of uncertainty to both the traditional and the rebate-type of insurance, as this is considered one of the barriers to insurance uptake and we are interested in analysing the effect of ambiguity attitudes have on WTP. The rebate-type does not reduce ambiguity, it increases ambiguity and removes a state of certainty. It is actuarially equivalent to the traditional insurance design. Assuming fully rational actors, there should thus be no difference in WTP for both designs. However, Serfilippi et al. (2016) predict a higher WTP for the rebate insurance design for subjects who are sensitive to certainty due to the disappearance of certainty. The idea being that they will now behave according to EU. There are 2 important theoretical differences: our experiment has risk and ambiguity and we do not measure sensitivity to certainty, but ambiguity attitudes and loss aversion. Moreover, our participants will indicate their WTP for only 1 of the two designs, instead of both designs. If we find evidence of our first hypothesis, than probabilistic sophistication is violated and with it Expected Utility theory. This would mean that at least for index-insurance markets with its inherent basis risk, Prospect Theory would be a better model for explaining decision-making under ambiguity. With no ambiguity, and with no certainty, it is possible that EU still holds. This is outside the scope of this research. More important is that we want to see whether the mechanism holds merit: whether the removal of certainty increases the WTP for the rebate index insurance type and which characteristics are related to this mechanism. This brings us to our final three hypotheses.
Our fourth hypothesis (4) states that ambiguity aversion and a-insensitivity are negatively correlated to WTP for both index-insurance types due to basis risk; this relation is less strong for the rebate type. Both insurance types include basis risk or ambiguity. We expect that ambiguity averse subjects have a lower WTP for index an insurance design. Experiencing a bad harvest and not receiving a pay-out is a highly unlikely loss and constitutes a worst-case scenario. This is exactly what pessimistic or ambiguity averse subjects dislike and try to avoid. This is magnified for those individuals that are more a-insensitive. A-insensitivity implies the overweighting of extreme probabilities. This overvalues the probability of basis risk occurring and thus lowers WTP. For the rebate-type the payment of the premium is also made uncertain, albeit only in a psychological way. If the premium is considered a loss, it has changed from a certain to a probable loss. On average subjects are ambiguity seeking for likely losses. This would result in a higher WTP for the rebate type, compared to the traditional type that knows a certain loss of the premium payment. However, the worst-case scenario remains there, of which the likelihood will be overweighted. Therefore ambiguity attitudes have a negative impact on WTP for both designs due to basis risk. But the relation to the rebate type is less strong, due to ambiguity-seeking tendencies for the premium payment.

Our fifth hypothesis (5) predicts that loss aversion is negatively correlated to WTP for the traditional index insurance, assuming a stand-alone investment frame. The reference point taken to evaluate gains and losses is pivotal in explaining insurance decisions. If farmers frame insurance as a simple lottery, i.e. a stand-alone investment, as argued by Babcock (2015) and Brown (2008), the reference point that signifies what constitutes a loss or a gain is the payment of the premium itself. A loss is experienced whenever the premium paid exceeds the pay-out. For both designs, this is the case when the harvest is good, or when the harvest is bad and the index is not triggered. Therefore, the probability of a loss under this frame is large. Relatively more loss averse individuals will thus have lower WTP for index insurance, if the stand-alone investment frame is assumed.

Our sixth and final hypothesis (6) states that WTP for the rebate-type insurance will be higher due to a framing effect; this relation will be stronger for the relatively more loss averse. A difference in WTP between two actuarially equivalent insurance designs could be explained by a change in frame that is assumed when evaluating the insurance design. Serfilippi et al. (2016) argue that for the rebate type insurance the certain loss is removed whose disutility was relatively overvalued. Thus making the overall utility of the rebate scheme insurance higher for those subjects that overvalue certainty.
3. Experimental Design and Methodology

In this section we give an overview of our sample and some descriptive statistics. We then present the experimental design and procedure of our three games. In the first two games we test for ambiguity attitudes and loss aversion. The loss aversion game followed the ambiguity game in a digital survey using tablets. In the third game we elicit the WTP of farmers for different types of insurance design using a framed lab-in-the-field experiment, meaning that it was a field experiment in the context of being a maize farmer, which was the main crop cultivated in our sample. Whereas the survey was presented to individual farmers, the WTP-game was played with a group of 8 to 14 farmers at the same time, depending on the size of the farmer group.

3.1: Sample

The data used for this thesis comes from a study conducted in Kenya in May 2017. In total 276 female farmers belonging to 13 different farmer groups in Meru County participated in the experiments. The 13 farmer groups selected have on average 20 members and have previously participated in a study conducted from October 2016 till March 2017. Additional data used, comes from this study that was conducted on in total 40 farmer groups. In October 2016, 19.9% of our sample were insured as a result of a randomly awarded free insurance, conditional on the purchase of certified improved seeds. The insurance type offered was a hybrid insurance: partially indemnity and partially index based. APA Insurance is the Kenyan insurance company that provided this insurance product. All subjects that did not participate in all three games, have been dropped from the data. We also dropped all subjects that were not present during the March household survey. For all remaining 276 subjects in this study, we have detailed information on individual, household and farm characteristics. In our sample, 100% of the respondents is female, with an average age of 44.4 years and 6 years of education. Household size averages at 5.7 persons average income from farming activities is 20592 Kenyan shilling (Ksh) a year.

Mobilisation was done by contacting the leaders of the farmer groups a week beforehand to set a meeting date. Every day we would visit one or two farmer groups, preferably on their meeting day to ensure a high turnout. The meeting place was often a primary school, a church, dispensary or an open field. We brought chairs for the WTP-game, so the subjects could sit comfortably. Randomisation was done by stratified sampling at the group level. Once everyone had arrived, we assigned the different groups. Farmers were randomly given a tag which said either I0-L, I0-G, I1-L or I1-G. ‘I0’ and ‘I1’ represent the assigned insurance design for the WTP-game, respectively the traditional type of index-insurance (I0) or the rebate type (I1). The ‘–G’ or ‘–L’ stands for the ‘Gain’ or ‘Lose’ scenario in the ambiguity game.

Table 1 shows that approximately half the sample played the lose scenario and the other half played the gain scenario of the ambiguity game. Similarly half the sample faced the traditional insurance and half the rebate type. In each village, all subjects played the same loss aversion game with no variation. By
stratified randomisation within every farmer group we solve for possible unobserved heterogeneity effects in our sample. This method also minimises selection bias, increasing the likelihood that the subsamples are representative of the population at large. If all subjects in one village would play the same game, village-specific unobserved variables might influence the results. For example some villages have more experience with insurance, are less poor, are more remote than other villages. By randomly stratifying in every farmer group, we control for those unobserved differences between the villages. The type of insurance design that would start was alternated every farmer group. The insurance type that did not start, would first do the survey module containing the ambiguity and loss aversion game.

<table>
<thead>
<tr>
<th></th>
<th>Gain</th>
<th>Losses</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Insurance</td>
<td>67 (I0-G)</td>
<td>69 (I0-L)</td>
<td>136</td>
</tr>
<tr>
<td>Rebate Insurance</td>
<td>71 (I1-G)</td>
<td>69 (I1-L)</td>
<td>140</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>138</td>
<td>138</td>
<td>276</td>
</tr>
</tbody>
</table>

Nine experienced enumerators, who were also part of the household surveys in October and March, explained the experimental protocols in Kimeru or Kiswahili and made sure the farmers were able to understand the games.⁶ Four of them were exclusively trained in the WTP-game, two for each type of insurance design. To avoid mistakes, the enumerators only presented one type of insurance design. The other five enumerators conducted the survey module. Once the first round was over, the groups switched. Farmers were instructed not to talk to each other to reduce information spill-over effects from one group to another. The enumerators were monitoring this and would fine subjects when disclosing information to one another. One round lasted approximately 45 minutes to an hour. In total the experiments took around 2 to 2 and a half hours depending on the farmer group size.

3.2: Incentives

Every subject plays 3 games, (1) the ambiguity game, (2) the loss aversion game and (3) the WTP-game. For every game money can be won dependent on their choices during the game and on luck. The participant received a voucher with the amount won for every game. Once all three games were completed, the vouchers were collected, put in a large jug and one of the vouchers was randomly selected which was paid out in cash to the subject.

Table 2 shows the maximum and minimum amounts that could be won in every game. The maximum amount that was paid out is 400 KSh. The minimum amount that we paid out is 250 KSh. Because luck plays a substantial role in all three games, we decided to not pay out less than 250 KSh. If a farmer was very unlucky in one of the games and also in picking the voucher, they were given the minimum of 250 KSh. This was only explained during the pay-out phase once all games had been completed, thus retaining the incentive to do your best and give reasoned decisions during the games. This solves ethical

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⁶ The local language was Kimeru, but sometimes enumerators had to communicate in another local language or Kiswahili.
concerns that arise from paying one subject more than 4 times more than another subject. The minimum amount won is slightly higher than the minimum wage for casual workers in 2015 in the agricultural industry in Kenya, which was set at 228.30 KSh a day (Africapay, 2015).⁷ In the next section we will describe in detail the experimental design, methods used and procedural details of the 3 games.

Table 2: Overview monetary reward per game

<table>
<thead>
<tr>
<th></th>
<th>Ambiguity</th>
<th>Loss Aversion</th>
<th>WTP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>350 KSh</td>
<td>400 KSh</td>
<td>350 KSh</td>
</tr>
<tr>
<td>Minimum</td>
<td>250 KSh</td>
<td>75 KSh</td>
<td>140 KSh</td>
</tr>
</tbody>
</table>

3.3: Game 1: Measuring Ambiguity Attitudes
As we analysed in the theoretical framework, ambiguity attitudes consist of ambiguity aversion and ambiguity generated likelihood insensitivity. The ambiguity game captures both concepts and is based on the methodology of Dimmock et al. (2015 and 2016). This method has been used in large household surveys and in lab experiments. The method has been slightly adjusted to ensure better understanding for the population under study. The ambiguity game uses 3 scenarios and subsequent variations on every scenario to estimate the ambiguity attitudes. We offered respondents real monetary rewards based on one of their choices in one of the scenarios. Half of the subjects played an ambiguity game where they could win 100 KSh, the other half could lose 100 KSh. To even out the average winnings of both groups, gain-participants received a participation fee of 250 KSh and lose-participants 350 KSh. Every participant could therefore finish the game with either 250 or 350 KSh.

The questions in our survey were similar to those in the famous Ellsberg experiment (1961). Rather than two urns with balls of 2 colours, we ask respondents to choose between an unambiguous box (box 1) and an ambiguous box (box 2).⁸ Because we could not bring computers with internet access into the field, we used non-transparent lunchboxes with coloured beads instead.⁹ Each box holds exactly 100 beads, The respondents were asked to choose one of the boxes to draw a bead from. If this bead was the winning colour, they would win 100 KSh. The contents of box 1 were known and shown to the participant. The contents of box 2 were unknown and hence ambiguous. The respondents only knew the amount of beads and how many different colours could be present in the ambiguous box. Besides stating a preference, respondents could also state to find both boxes ‘equally attractive’ which is the same as ‘indifference’ in Dimmock’s terminology.¹⁰ In scenario 2 and 3 the amount of beads remains 100, but instead of only 2 colours, the boxes contain beads of 10 different colours to simulate situations of high or low likelihood. We will first explain the procedures of the game for the gain scenarios. Then we explain how ambiguity indices can be constructed from the results of the game. Finally we show how the game was set up for the lose scenario.

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⁷ During the recent Labour celebrations a minimum wage increase has been announced of 18%. Hakizimana et al (2017) talk about a minimum wage of $3.33 per day which translates to 333 KSh per day.
⁸ Dimmock et al use box K for the known box, and box U for the unknown or ambiguous box.
⁹ We used the small coloured beads that are famously used for Kenyan jewellery.
¹⁰ We named this option equally attractive, to reduce any negative connotations of disinterest from the respondents, indifference might imply when translating to Kimeru.
**Elicitation Procedure**

In the first scenario, box 1 contains 50 green and 50 yellow beads. Box 2 contains 100 beads of either green or yellow colour with an unknown composition. The participant wins if a green bead is drawn. There could be between 0 and 100 green beads in box 2. Following Dimmock et al. (2015), Baillon and Bleichrodt (2015), Baillon et al. (2015) and many others writing on ambiguity, we employ matching probabilities to estimate ambiguity attitudes. A matching probability ($m$) is the objective probability for which an agent is indifferent between the risky option and the ambiguous option. For our game this means that $m$ is the indifference between winning 100 KSh under the ambiguous option (box 2) and winning 100 KSh with probability $m$ for the risky option (box 1). We elicited $m$ using a sequence of questions, while changing the colour ratio of beads in box 1, for which the respondent had to state their choice: box 1, box 2, or equally attractive (see Figure A1 in Appendix A for a graphical representation).

In theory it is possible that a non-neutral response to the first round of scenario 1, can be reconciled with subjective expected utility theory if the subject assigned a very low subjective probability to drawing a green bead from box 2. Abdellaoui et al. (2011) and Dimmock et al. (2016) therefore give subjects the opportunity to alter the winning colour in box 2. They find that less than 2 percent of the respondents changed the winning colour in box 2. Dimmock et al. (2015) also test this by allowing respondents to choose the winning colour of the whole game. Fewer than 1 percent opted for this. All three studies show that people are indifferent about the winning colour and there were no significant differences in the mean matching probabilities of the group that was allowed to switch colour and the group that could not switch. We therefore did not allow respondents to change the winning colour.

If the respondent’s response was ‘equally attractive’, the survey continued with the second scenario. If the respondent indicated that box 1 was preferred, then the enumerator replaced some of the green beads with yellow beads, reducing the known winning probability of box 1. If the respondent indicated that box 2 was preferred, then some of the yellow beads of box 1 were replaced by green beads, increasing the observable winning probability of box 1. Whenever the subject selects box 1, this box is made less attractive. Whenever the subject selects box 2, box 1 is made more attractive. The content of box 2 were never changed, never visible and remained ambiguous throughout.

Changing the ratio of beads was done by method of bisection as explained in the annex of Dimmock et al. (2016). After every choice, the difference between the lower bound and the upper round on the matching probability is reduced by half. This would continue until the answer ‘equally attractive’ was given or until a maximum of three additional rounds. After the final round, the matching probability is the objective probability of box 1 if the respondent answered equally attractive, otherwise the midpoint of the average of the lower and upper bound of the final round is taken.

**Estimating Ambiguity Aversion**

Subjects that find both boxes equally attractive in the first round, where the objective probability of winning in box 1 is 50%, are ambiguity neutral. This means that the respondent treats the ambiguous
box (2) as having the same percentage of winning as the known box (1), i.e. 50% chance of drawing a green bead. Hence the matching probability $m$ is 0.5. If the respondent preferred box 1 over box 2, then the respondent is ambiguity averse with $m < 0.5$. Respondents that choose box 2 over box 1 in the first round are ambiguity seeking with $m > 0.5$.

The literature on ambiguity predicts that ambiguity aversion is dependent on the likelihood of the event. Dimmock et al. (2016) give proof in a large representative household sample that people respond differently to situations if the likelihood of winning is 50-50, very high or very low. On average people are average ambiguity seeking for low likelihoods and ambiguity averse for high likelihoods of winning. We therefore include a scenario with a low likelihood and one with a high likelihood of winning. Other methods to estimate ambiguity attitudes like Baillon & Bleichrodt (2015), employ a similar strategy.

Our second scenario has a very low likelihood of winning in the starting scenario, i.e. 10%, whereas the third scenario has a very high likelihood of winning, i.e. 90%. Both the second and the third scenario are played with 100 beads of 10 different colours.

For the second scenario, In box 1, there are 10 beads of every colour and 100 beads in total. The respondent wins if a green bead is drawn from the box, thus giving a winning chance of 10%. If any colour other than green was drawn, the respondent would not win. After every choice of the respondent, the composition of the beads in box 1 would be altered using the same method of bisection. For the third scenario, the starting situation is the same as the second scenario, but the winning condition is different. Now, the respondent wins if the bead drawn is NOT green, resulting in a 90% winning probability. Similarly, after every choice, the composition of the beads in box 1 is rearranged using the method of bisection until the matching probability is found. The second and third scenario provides us with information on whether ambiguity aversion is dependent on likelihood. Together with the matching probability of scenario 1, we can construct indices of ambiguity aversion for moderate, very low and very high likelihoods of winning. The indices that are used in this study are calculated as follows.

We will denote $AA_{50}^+$ as the ambiguity aversion index for the first Gain scenario where the objective winning probability $p$ of box 1 in the starting situation of scenario 1 was 50%. Likewise, we let $AA_{10}^+$ refer to the ambiguity aversion index for scenario 2, and $AA_{90}^+$ for scenario 3. The index is calculated by deducting the matching probability from the objective winning probability of box 1 in the first round of the scenario: $AA^+ = p - m$. This leads to the following ambiguity aversion indices:

$$AA_{50}^+ = 50\% - m_{50}$$  
$$AA_{10}^+ = 10\% - m_{10}$$  
$$AA_{90}^+ = 90\% - m_{90}$$

Positive values of $AA^+$ imply ambiguity aversion. Negative values imply ambiguity seeking and $AA^+=0$ signifies ambiguity neutrality.
Check questions and Pay-Out

After the three scenarios were answered, the survey included 2 check questions to test whether the participants behave consistently. The matching probability of the first scenario was taken as a starting point. For \( m = 0.5 \), the respondent was indifferent between box 1 and box 2, with an objective winning percentage 50\% for box 1. The check questions take the matching probability of the first scenario and do this -10 and +10 winning beads. In our example, the first check question recreates scenario 1 with 40 winning beads for the first question and 60 winning beads for the second question. For the first question, to be logically consistent, the respondent should answer that box 2 is preferred, for the second question box 1 should be preferred. These questions will be important for analysing whether the respondents understood the game and behave consistently.

After answering the sequence of questions for all three scenarios, the tablet would randomly select one of the three scenarios to be played out for real. This meant that after having selected one of the three scenario’s, one of the situations answered by the respondent was randomly selected. The respondent would win if the bead had the winning colour. If the respondent’s answer was box 1, then the selected situation was recreated from which a bead was drawn. If the respondent said box 2, then the respondent would draw a bead from box 2. If a situation was selected that was answered with equally attractive, then the enumerator would let the respondent draw a bead from box 1.

Estimating A-insensitivity

The second component of ambiguity attitudes is a-insensitivity or ambiguity generated likelihood insensitivity. A-insensitivity is a measure of how well one distinguishes between changes in likelihood or whether one perceives ambiguous likelihoods as mostly 50-50 situations. Theory predicts that people overweight the probability of highly unlikely events and underweight the probability of highly likely events to occur. The second and third scenario provides us with information on how sensitive farmers are to different likelihoods. We can construct the following A-insensitivity index. We use the ambiguity aversion index for the second and third scenario. The objective winning probabilities of scenario 2 and 3 add to 100\%. They are composite events, meaning that also the matching probabilities should add to 1 if completely neutral and rational. We can thus measure a-insensitivity:

\[
AI^+ = AA90^+ - AA10^+
\]

Positive values of \( AI^+ \) mean that the subject is a-insensitive. Negative values signify a-oversensitivity. Neutral respondents have ambiguity indices of 0 and their measure of \( AI^+ \) will therefore also be equal to 0.

Ambiguity attitudes for Losses

Half of the sample played the ambiguity game with the prospect of losing 100 KSh. Their participation fee was higher to encompass a possible loss. The aim is to determine whether ambiguity attitudes for

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\(^{11}\) If the respondent did not agree with this, the enumerator could also select a bead from box 2.
prospective losses are different from prospective gains. The three scenarios remain exactly the same. Only the winning condition changes from ‘win’ to ‘lose’. Hence where one could win if a green bead is drawn, in scenario 1 and 2, now the respondents lose if a green bead is drawn. Consequently, for scenario 3, one loses if a green bead is NOT drawn, meaning that for every other colour than green, one loses. This translates into objective losing probabilities for box 1 of 50%, 10% and 90% for the three scenarios. The ambiguity indices for losses are constructed as follows:

\[ AA50^- = m^{50} - 50\% \]
\[ AA10^- = m^{10} - 10\% \]
\[ AA90^- = m^{90} - 90\% \]

Similar to that the ambiguity index for aversion is a reversal of the one for gains (\(AA50^+ = 50\% - m^{50}\)). The a-insensitivity index for losses is also reversed.

\[ AI^- = AA10^- - AA90^- \]

In the second losing scenario \(AA10^-\), there is actually a not losing probability of 90%. Similarly the third scenario, there is a not losing probability of 10%. So the second scenario has the same winning probability as the third gain scenario, and the third losing has the same as the second gain scenario. If we want to measure insensitivity to likelihood for losses, or the tendency to reduce probabilities to 50-50 scenarios, we need to adjust the equation accordingly.

Practicalities

In previous studies, these experiments have mainly been conducted with university students or in a general survey on the American population. This is the first time that such an abstract experiment is done on a population that is arguably less educated and less exposed to probabilistic concepts in daily life. Most respondents are poor female farmers with little education or even illiterate. We therefore tried to keep the experiment as simple and visual as possible. Enumerator followed a fixed script on the tablet reiterating every round the winning/losing condition, the amount of beads of every colour in box 1, the amount of beads in box 2 and changes in the ratio of beads in box 1. The actual content of box 1 throughout the various rounds was visualised on a white plastic plate. There the enumerators recreated the constellation of the coloured beads in play at the moment so that the respondent could clearly see the colours in play. If it was still not clear to the farmer, the enumerator had a picture of every possible situation on their tablet, that they would show to the farmer. It was not uncommon that an enumerator explained the game multiple times before the respondent understood the game.

The lunchboxes with beads were checked every night and given to another enumerator the next day to minimise enumerators’ knowledge of the contents of the ambiguous boxes. Every 4 days, we removed all the beads from the boxes and randomly filled the ambiguous boxes with beads. We used two big jugs to fill with green/yellow beads and beads of ten different colours. After shaking the jugs, we poured the beads into the ambiguous boxes until the exact amount of 100 beads. In total there were 3 boxes per
enumerator. One box 1, and two times a box 2. One ambiguous box for scenario 1 and one ambiguous box for scenario 2 and three.

3.4: Game 2: Measuring Loss Aversion
The second part of our survey module aims at eliciting loss aversion of subjects in risky choices. Similar to the elicitation of ambiguity attitudes, this experiment also asks subjects to choose between two options. To reduce the cognitive burden on our participants, we ask as little questions as possible while still providing a (rough) estimate of loss aversion. We follow Gächter et al. (2010) and Fehr and Goette (2007) who use a simple lottery choice task to measure loss aversion. The subjects are faced with 6 simple choices between a 50-50 chance of a win of 150 KSh fixed throughout the choices or a loss of 50 KSh going up to 175 KSh. For all 6 choices, respondents have to indicate whether they ‘accept’ or ‘reject’ the game (see Figure A2 for an overview of the lottery choices). In every subsequent choice the amount lost is augmented with 25 KSh, starting at 50 KSh. In case they reject, nothing happens. According to Rabin (2000) and Wakker (2005), this method measures loss aversion in risky choices.

Procedural details
The subjects were shown a 40 KSh coin and if needed also an image on the tablet to make the rules of the game very clear (see Figure A3 for an example). The subjects were explained that at the end of the 6 questions, one of the questions would be randomly selected to be played for real. Their answer, accept or reject, would determine whether the coin would be flipped. If the answer was accept, the coin would be flipped, if it turns up heads, the subject would win 150 KSh. However, if it turns up tails, the subject would lose the amount specified by the selected question.

As it is arguable unethical to allow our subjects to actually lose money, we told them that they would be awarded 250 KSh for participating regardless of their choice. Any wins or losses would be added or deducted to their participation fee. Our subject pool had already been exposed to a flipping of the coin experiment. During a household survey in October subjects faced an investment game where a similar flipping of the coin game was played. This previous exposure contributed to better understanding of the concept of flipping a coin and the rules of the game.

Estimating Loss Aversion
According to Gächter, this method above measures loss aversion rather than risk aversion (Gächter et al., 2010, 8). They claim that due to the small-stakes, risk aversion derived from these choices would imply absurdly high degrees of risk aversion in high-stake gambles. According to Rabin (2000) Under EU subjects should accept the questions #1 to #5 and reject question #6. Question 1-5 all have a non-negative expected value and any rejections of these questions are indicative of loss aversion under EU.

Using cumulative prospect theory (see theoretical framework) we can simply measure loss aversion by taking the following indifference equation:

\[ \omega^+(0.5)v(G) = \omega^-(0.5)\lambda_1 v(L) \]
In this equation $G$ signifies the gain or the fixed amount won in every choice. $L$ represents the loss of the choice. $v(x)$ is the utility of the outcome $x$ which can be either $G$ or $L$. $\lambda$ is the coefficient of loss aversion. $\omega^+$ and $\omega^-$ are probability weights for gains and losses. We will apply varying assumptions with regard to the probability weighting function. We will first, for the sake of simplicity, estimate $\lambda$ assuming that subjects have the same probability weighting function for gains and losses, i.e. $\omega^+(0.5)/\omega^-(0.5) = 1$. A second assumption is that diminishing sensitivity, a key tenet of prospect theory, does not play a role. Gächter et al. (2008) argue that for small stakes diminishing sensitivity can be neglected which they base on a study by Fehr-Duda et al. (2006) who predominantly find linear value functions for small stakes. For our study this means that for the range of losses considered, sensitivity should not be greatly different.

With our assumptions, the measure of loss aversion is reduced to $\lambda_1 = G/L$. In this simple equation $G$ is the fixed gain of 150 and $L$ is the latest choice lottery still accepted by the subject. Assuming monotonicity of subjects’ answers, meaning that a subject did not accept a game after already rejecting a previous game, loss aversion can be easily calculated. If a subject accepted all choices, even the last one with a loss prospect of 175 KSh, the estimate of loss aversion would be $\lambda = 150/175 \leq 0.86$. If the subject is not loss averse and thus accepting question 1 till 5, $\lambda = 150/150 = 1$. If all lotteries are rejected $\lambda = 150/50 \geq 3$. Here, $L$ takes on the lowest possible loss in our series of choices even though this was not accepted. This makes the loss aversion coefficient greater or equal to 3. Using this method, loss aversion can be estimated for individuals.

**Stricter assumptions**

We will also estimate loss aversion taking reasonable estimates of probability weights and diminishing sensitivity from the literature. Booij and van de Kuilen (2009) give an overview of the literature on the parameters for the probability weighting function and the value function since the original paper of Kahneman and Tversky. They also give their own estimates based on a study conducted on a representative sample of the general public of $N=1,935$. Following Gächter et al. (2010), we can include some of PT’s assumption to get a better estimate $\lambda$, giving us the following equations:

$$\lambda = \omega \cdot \left( \frac{G^\alpha}{L^\beta} \right)$$

$$\omega \equiv \omega^+(0.5)/\omega^-(0.5).$$

In this equation $\alpha$ and $\beta$ represent diminishing sensitivity for gains and losses respectively and $\omega$ represents probability weighting for gains and losses. Gächter et al. (2010) take $\omega=0.86$, based on a study by Abdellaoui (2000), which is the largest difference between probability weighting for gains and losses that they could find in the literature. The probability weighting function is often described by two properties: sensitivity towards probabilities and pessimism, which give it the elevated inverse-$S$ shape (Booij and van de Kuilen, 2009). Assuming Prospect Theory rather than a Multiple Prior model, this is...
essentially what we capture in our ambiguity game. As we expect to find strong pessimism and likelihood insensitivity, stronger than in most samples on Western populations, it seems appropriate to take the estimate $\omega=0.86$ of Abdellaoui (2000). Tversky and Kahneman (1992) estimated $\omega=0.933$ and Booij and Van de Kuilen (2009) find $\omega=0.966$. For diminishing sensitivity Gächter et al. take $\alpha=0.95$ and $\beta=0.92$, following Booij and van de Kuilen (2007). In a review of all estimates of Prospect Theory’s parameters Booij and Van de Kuilen, report that most contemporaneous studies find diminishing sensitivity parameters to lie between 0.8 and 1 (2009). Themselves they find, using maximum likelihood estimation, $\alpha=0.859$ and $\beta=0.826$, whereas Tversky and Kahneman (1992) reported $\alpha=\beta=0.88$. In a second estimation of loss aversion we therefore take $\omega=0.86$ and $\alpha=0.859$ and $\beta=0.826$ to be reasonable estimates for our study, giving us the following equation:

$$\lambda_2 = 0.86 \times \left( \frac{G^{0.859}}{L^{0.826}} \right)$$

Finally, we will try to estimate loss aversion using the results of the ambiguity game to estimate the parameters of the probability weighting function. According to Booij and Van de Kuilen (2009), the most commonly used specification is Goldstein and Einhorn’s (1987) linear-in-log-odds specification, which is noted as:

$$\omega(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}$$

In this equation $\delta$ represents pessimism, or the elevation of the intercept away from 0 of the value function. This is captured by our estimate of ambiguity aversion of the first scenario of the ambiguity game for gains and losses. $\gamma$ represents the curvature of probability weighting function, resulting in its inverse-S shape. This we essentially capture with our estimate of a-insensitivity, which is derived from the second and third scenario of the ambiguity game. Assuming $\omega \equiv \omega^+(0.5)/\omega^-(0.5)$, we can estimate this using the data from the ambiguity game. We then get the following equation to estimate loss aversion

$$\lambda_3 = \hat{\omega} \times \left( \frac{G^{0.859}}{L^{0.826}} \right)$$

For all 3 estimates of loss aversion, we will report the median as is commonplace in the literature. This also holds for our estimates of $\delta$ and $\gamma$.

### 3.5: Game 3: eliciting WTP for Insurance designs
In our third game, we seek to elicit the willingness-to-pay for two different index insurance designs. The game is inspired on the by the WTP-game of Serfilippi (2016), extending it by introducing basis risk. The game is a framed field experiment, meaning that the context of the experiment is framed in a way that would be familiar to the subjects. 90% of our sample uses at least parts of their land for maize.
We therefore designed this game to simulate a realistic scenario for a maize farmer in rural Kenya. Half of our sample faced a traditional index insurance design, the other half faced a rebate-type design, where the farmer only had to pay the premium when the year was good. For this rebate-type the premium would get deducted from the insurance pay-out for bad harvests. Both insurance contracts were presented as rainfall index insurances. This means that the insurance company collects local rainfall data. Whenever the rainfall was below a certain threshold in a specific region, all the farmers in that region would get a pay-out. In Kenya, this is measured by a weather station located in every state-owned primary school in Meru county. One of the main problems with this technology is basis risk, the possibility that the weather station measures a state of the world which is different from individual farmer’s reality. If the index is not triggered, but the farmer experienced a drought, his yield will be bad and the insurance will not pay out. For the sake of simplicity, we eliminated the possibility of upside basis risk, which signifies the possibility of receiving a pay-out while also realizing a good yield.

WTP elicitation was done using an adapted Becker-DeGroot-Marschak mechanism. This method was developed by Becker et al. (1963) and is often used in experimental settings. Subjects indicate the maximum price they are willing to pay for the insurance. The true price is then randomly determined. If the true price was lower or equal to the WTP of the subject, they will purchase the insurance for the true price. If the true price is higher than the WTP of the subject, the subject will not purchase insurance. Rather than randomly selecting the true price, we used a fixed price. The respondents were however not aware of this and were told that it would be randomly selected within a given range. To avoid anchoring effects from the household survey WTP-elicitation, we provided a range wherein the true price must lie. The farmers were told that the true price of the insurance would lie between 400 and 1,600 KSh and would be randomly selected. The first question starts at the upper boundary of the given range. Upon rejection, the price is decreased by 1/4th of the upper boundary until the subject accepts the price given. From this point a method of bisection was used, similar to the one used for matching probabilities, until a precision of 50 KSh was achieved. If a subject accepted the upper boundary of 1600 KSh, a follow-up question ensued where they were asked to state their maximum WTP. Similarly, if the subject was not willing to pay the lower boundary, a follow-up question elicited their maximum WTP. Whether or not the subject purchased insurance had a direct impact on how much money could be won in the game.

Our sample of farmers were included in the previously mentioned study from October 2016 till March 2017. 19.9% of our sample was insured by APA Insurance at the time we conducted this research. This could mean that they have more information and experience with the price and concept of insurance. According to APA Insurance, all farmer groups included in our sample have been introduced to the concept of index insurance before and are to some level aware of how it functions. There is thus a possibility that farmers will anchor their stated WTP to the prices previously communicated to them by APA. Moreover, during the March 2017 outreach, respondents were asked to state their willingness-to-pay for the hybrid index-insurance product offered by APA Insurance. WTP was elicited by use of the...
BDM-method, using a random selection of the true price from an envelope (between 100 and 400 KSh.). An advantage of this is that the farmers have had previously experienced the BDM-method, enhancing understanding of the rules of the game. A drawback is that some of the farmers, especially those who ‘won’ this game, might anchor to this price. To try and avoid anchoring to these previous prices, we explicitly instructed the participants that the true price of the game would lie between 400 KSh and 1600 KSh, of which the lower boundary is equivalent to the highest possible price they could have paid during the March WTP-game.

Experimental set-up
Subjects only played one of the two insurance designs. In one session between 6 and 14 farmers participated, depending on the size of the farmer group. Two well-trained enumerators carefully explained the procedures and rules of the games complemented by visual aids. All groups received the same amount of extensive information about the rules of the game, regardless of their previous experiences. Farmers were explained their starting situation, which was the same for everybody: You are a farmer with 1 hectare of land which you use solely for maize production and with 5,000 KSh in savings, which can be used to purchase insurance or not. Savings, yields, net revenues and insurance pay-out are based on historical yields and on data provided by APA insurance and Shalem, a local production inputs provider. The exact values are constructed in a way that is easy to calculate and simple to understand to avoid unnecessary confusion.

The yield is dependent on weather and it can either be a good yield (p) or a bad yield (q). A good yield occurred with p=0.8 and was set to 1750 kg of maize and a bad yield with probability q=0.2 harvesting 500 kg of maize. The revenue in both states of the world, is dependent on the price of maize. Due to the effects of supply and demand, the price of maize will be higher in a bad year than in a good year. This is because weather related shocks are covariate. When there is too little rain, everyone’s yield will on average be worse, driving up the price for maize. In the experiment the price of maize in a good year was set to 20 KSh/kg and in a bad year it was 30 KSh/kg. At the time of the experiment, the drought that affected Kenya, drove up the price of maize to 40 KSh/kg. Gross revenue was therefore either 35,000 or 15,000. All farmers are assumed to face a fixed amount of production costs, which was set to 15,000 KSh. To avoid confusion, we only communicated the net revenues in both states of the world and how they were derived, i.e. 0 KSh in a bad year and 20,000 in a good year. Yields and production costs were mentioned in the introduction to provide a realistic farming scenario for the farmers. The net revenue after the harvest realisation plus the remainder of the savings equals the subject’s Final Household Money. This final outcome would determine the amount won in the game and is therefore dependent on both the insurance decision and on luck. Before knowing the outcome of the harvest, farmers had the opportunity to purchase insurance from their savings, which would pay out if the yield was bad. In the traditional index insurance contract, the premium was paid independent of the yield and deducted from their savings. In the rebate-contract the premium was only paid if the yield was good.
The insurance pay-out was set to 5,000 KSh, which would only be paid out if the yield was bad. For the rebate-contract the premium would be deducted from the insurance pay-out, making both insurance contracts actuarially equivalent as can be seen in Table 3-5. For the sake of simple calculations in the Tables a price of 1,000 KSh is assumed, which is the actuarially fair price if there is no basis risk. The only difference is in the framing of the contract. It is important to realize that this experiment assumes no changes in liquidity constraints, trust, basis risk, nor do we reduce ambiguity.

Table 3: Overview income without insurance

<table>
<thead>
<tr>
<th></th>
<th>GOOD YIELD</th>
<th>BAD YIELD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Savings</td>
<td>5000</td>
<td>5000</td>
</tr>
<tr>
<td>Net Revenue</td>
<td>20000</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total money</strong></td>
<td><strong>25000</strong></td>
<td><strong>5000</strong></td>
</tr>
<tr>
<td>Real money won (=TFM/100+100)</td>
<td>350 KSh</td>
<td>150 KSh</td>
</tr>
</tbody>
</table>

Table 4: Overview income with insurance (type 0, traditional)

<table>
<thead>
<tr>
<th>Insurance Price = 1,000 KSh</th>
<th>GOOD YIELD</th>
<th>BAD YIELD</th>
<th>BAD YIELD &amp; BAD INDEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Savings</td>
<td>4000</td>
<td>4000</td>
<td>4000</td>
</tr>
<tr>
<td>Revenue</td>
<td>20000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Insurance pay-out</td>
<td>0</td>
<td>5000</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total money</strong></td>
<td><strong>24000</strong></td>
<td><strong>9000</strong></td>
<td><strong>4000</strong></td>
</tr>
<tr>
<td>Real money won (=TFM/100+100)</td>
<td>340 KSh</td>
<td>190 KSh</td>
<td>140 KSh</td>
</tr>
</tbody>
</table>

Table 5: Overview income with insurance (type 1, rebate)

<table>
<thead>
<tr>
<th>Insurance Price = 1,000 KSh</th>
<th>GOOD YIELD</th>
<th>BAD YIELD</th>
<th>BAD YIELD &amp; BAD INDEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Savings</td>
<td>4000</td>
<td>5000</td>
<td>4000</td>
</tr>
<tr>
<td>Revenue</td>
<td>20000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Insurance pay-out</td>
<td>0</td>
<td>4000</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total money</strong></td>
<td><strong>24000</strong></td>
<td><strong>9000</strong></td>
<td><strong>4000</strong></td>
</tr>
<tr>
<td>Real money won (=TFM/100+100)</td>
<td>340 KSh</td>
<td>190 KSh</td>
<td>140 KSh</td>
</tr>
</tbody>
</table>

Procedural details
During the introduction round, all possible scenarios and mechanisms were explained and most importantly the monetary incentives were clarified. The respondents were shown a plastic jug, which contained green and red ping-pong balls. A green ball represents a good yield, a red ball represents a bad yield. The enumerator explained and demonstrated that there are 4 green balls and 1 red ball, making the probability of a bad yield 0.2. After carefully explaining the outcomes in both states of the world with no insurance, the subjects were introduced to the insurance design they were assigned to and how it works. In both designs, we included basis risk which was set to 0.2. Basis risk was explained by showing the farmers a second plastic jug, which also contained red and green balls. The enumerators
did not show the content or ratio of the balls, creating ambiguity. They explained that if you purchased insurance and experienced a bad yield, the insurance would only pay out if a green ball was extracted from the index-jug. If a red-ball was extracted, then the insurance would NOT pay out even though you purchased insurance. The subjects were carefully explained how much final household money they would end up with in the various possible scenarios. Every participant would earn as a basis 100 KSh for participating, on top of that they would earn the Total Family Money received after playing divided by 100. If they decided to NOT purchase insurance, they would earn either an additional 250 KSh if they drew a green ball, or 50 if the ball drawn was red. If they did purchase insurance, a green ball means 240 KSh, a red ball means either 90 KSh if the index ball was green and 40 KSh if the index ball was red. The maximum that could be won was 340 KSh, the minimum 140 KSh.

Before drawing any balls from the jug(s), the respondents had to indicate their maximum WTP for the insurance design they faced. If the price they stated was higher or equal to the ‘true price’ of the insurance, then they would have purchased insurance which would then be applied to the pay-out round. The farmers were told that the true price of the insurance would lie between 400 and 1,600 KSh and would be randomly selected. Without basis risk, the actuarially fair premium would be 1,000 KSh. Including basis risk, the actuarially fair premium is 5000/(1/0.16)= 800 KSh. We used this price as the true price in the envelope which would be revealed after everyone stated their WTP. Whenever someone indicated their WTP to be equal or higher than 800 KSh, they had to pay the price of 800 in the envelope. Farmers were not aware of the exact amount of balls or ratio in the index-jug, making it an ambiguous situation. Understanding was tested by the enumerators by repeatedly asking questions to see whether they knew how much money they would earn in the different scenarios. The enumerators emphasised that the research was independent of APA Insurance and was solely for research purposes. Their individual answers would not be exploited for commercial purposes. It was also stressed that the subjects were not actually bidding for an insurance in real life, but were going to play a game in which their decision to purchase or not would influence the pay-out in the final round. Once all subjects understood, they were asked to step out of the group and to state their maximum WTP. This reduced the possibility of anchoring to the answers given by the people before them. Enumerators would follow the adapted BDM-method as indicated on their tablet and the answers were recorded digitally and on paper. Once all of the farmers stated their price, the enumerators revealed the true price, which was set at the actuarially fair price of 800 KSh. Everyone who indicated their maximum WTP to be 800 or higher, had to purchase the insurance at that price. Those facing the traditional contract had to pay this amount with their savings, represented by wooden coins. Those facing the rebate-contract only had to pay if the ball extracted was green. Once it was clear who had bought insurance and who had not, the pay-out round started. In this round, everyone got to extract a ball from the yield-jug and if red and insured also a ball from the index-jug. The winnings of the game were determined by the balls drawn and was written on a voucher consistent with the previous games.
3.6: Methodology

With the results of the ambiguity game and loss aversion game we can test the first three hypotheses that concern the pattern of ambiguity attitudes and degree of loss aversion of Kenyan farmers.

**Hypothesis 1:** Ambiguity attitudes of Kenyan farmers will differ for gains and losses. On average, farmers will be ambiguity averse for likely gains and unlikely losses and ambiguity seeking for unlikely gains and likely losses.

We test this by grouping our measures of ambiguity aversion as a dependent variable and regressing it on a dummy which takes the value of 1 if the loss attitudes were obtained and 0 otherwise, while controlling for age, years of education, household size and farmer group. This test is essentially a test for reference-dependence, which means that gains and losses are evaluated differently. If there is no reference-dependence then the ambiguity attitudes for gains and losses are the same. If the coefficient of the dummy variable $\beta_3$, in the equation below, is significantly different from zero, we can confirm that ambiguity attitudes differ for gains and losses and thus that there is reference-dependence.

$$AA = \beta_1 + \beta_2 AI \quad + \beta_3\text{loss}_{dum} + \beta_4\text{age} + \beta_5\text{educ} + \beta_6\text{hhsiz}e + \beta_7\text{farmergroup}$$

We also test whether $\beta_3$ is significant for our measure of a-insensitivity, using the equation below. When regressing ambiguity aversion we control for a-insensitivity and vice versa.

$$AI = \beta_1 + \beta_2 AA \quad + \beta_3\text{loss}_{dum} + \beta_4\text{age} + \beta_5\text{educ} + \beta_6\text{hhsiz}e + \beta_7\text{farmergroup}$$

Whether our sample is on average ambiguity averse for likely gains and unlikely losses and ambiguity seeking for unlikely gains and likely losses will be tested using the mean estimates and t-testing. Even though we randomised the selection of the gain/loss scenario and type of insurance at the individual level, we will control throughout our study for robust standard errors clustered at the group level. If there is no intra-group correlation this is equivalent to taking robust standard errors.

**Hypothesis 2:** A-insensitivity will be higher for our sample than for samples from similar studies in Western countries.

We test our second hypothesis by testing whether our measure of a-insensitivity is significantly higher than the measure obtained by Dimmock et al (2015), who find in a large representative sample of the U.S. population an estimate of $AI=0.320$.

**Hypothesis 3:** Kenyan farmers will be significantly loss averse

We test our third hypothesis with the results of our loss aversion game. We will perform a one-sided t-test on whether our estimate of loss aversion is significantly larger than 1. If significant, we confirm hypothesis 3. We will also test some assumptions of Prospect Theory to explore whether it is an appropriate model for explaining insurance decisions of subsistence farmers in Kenya. Besides the reference-dependence test, we will test for linearity of the probability weighting function, a reflection
effect, meaning that the ambiguity attitudes for losses are a mirror image of those found for gain. If we confirm hypothesis 1-3 and we also find probability weighting and a reflection effect, we have reasons to believe that Prospect Theory is a suitable decision model to try and understand the insurance decisions of Kenyan farmers.

**Hypothesis 4:** Ambiguity aversion and a-insensitivity are negatively correlated to WTP for both index-insurance types due to basis risk; this relation is less strong for the rebate type.

**Hypothesis 5:** Loss aversion is negatively correlated to WTP for the traditional index insurance, assuming a stand-alone investment frame.

**Hypothesis 6:** WTP for the rebate-type insurance will be higher due to a framing effect; this relation will be stronger for the relatively more loss averse.

The results of the WTP-game will be combined with the data on ambiguity attitudes and loss aversion to test our fourth, fifth and sixth hypothesis. Firstly, we test whether there is a significant difference between the two types of insurance design by performing an OLS regression of WTP on our rebate dummy variable. This dummy takes the value of 1 if the rebate type of insurance was offered and 0 if the traditional type of insurance was offered. We include our measures obtained from the ambiguity and loss aversion games as well as our control variables age, education, household size, farmer group, whether they have Mpesa, i.e. a mobile Kenyan bank, and whether they were currently insured by APA. Having a mobile bank account is positively correlated to WTP and is used as a proxy to control for financial literacy.

\[
\text{wtp} = \beta_1 + \beta_2 \text{AA} + \beta_3 \text{AI} + \beta_4 \lambda + \beta_5 \text{rebate\_dum} + \beta_6 \text{educ} + \beta_7 \text{age} + \beta_8 \text{mpesa} + \beta_9 \text{insured} + \beta_{10} \text{farmer\_group}
\]

Secondly, we will analyse whether specific people have a significant higher WTP for either design. We use the measures of ambiguity aversion, a-insensitivity and loss aversion to construct dummy variables. AAverse takes the value of 1 if the respondent is ambiguity averse for the first ambiguity question, meaning that \( AA50^+ \) is larger than 0. Similarly Ainsens takes the value of 1 if the respondent has a-insensitive and 0 otherwise. This implies that for other behaviours such as ambiguity-seeking, neutral, a-oversensitive and a-neutral behaviour the dummy is 0. For loss aversion we construct a dummy variable that is 1 for all subjects with an estimate larger than 2. This includes all respondents who only accepted the first question or who rejected all questions of the loss aversion game. By regressing WTP on these dummies, the rebate dummy and our control variables, we can find more information on which behavioural aspects contribute to a higher or lower WTP for index insurance. Finally, we analyse whether there are interaction effects between our behaviour dummies and the type of insurance offered.
4. Results and Analysis

4.1: Ambiguity Game

The results of the ambiguity game are shown in Table 6. $AA50^+$ is the estimate of ambiguity aversion for gains for the objective winning probability of 0.5. $AA10^+$ and $AA90^+$ represent the estimate of ambiguity aversion for respectively low and high likelihoods and are used to calculate a-insensitivity for gains $AI^+$. Likewise $AA50^-$ and $AI^-$ represent the same but are derived from the respondents that played the losing scenario of the ambiguity game. Table 7 shows the distribution of behaviour towards ambiguous situations for the three different levels of likelihood measured. The dominant behaviour is in bold. We compare our results with those obtained from a study that on a representative sample of the U.S. population (N=2991), which are also shown in Table 7 (Dimmock et al., 2015).

### Table 6: Estimates Ambiguity game

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Robust Std. Err.</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$AA10^+$</td>
<td>-0.23993</td>
<td>0.022225</td>
<td>-0.28835 -0.1915</td>
</tr>
<tr>
<td>$AA50^+$</td>
<td>0.10413</td>
<td>0.028567</td>
<td>0.041889 0.166372</td>
</tr>
<tr>
<td>$AA90^+$</td>
<td>0.277065</td>
<td>0.017137</td>
<td>0.239726 0.314404</td>
</tr>
<tr>
<td>$AI^+$</td>
<td>0.516993</td>
<td>0.024489</td>
<td>0.463635 0.570351</td>
</tr>
<tr>
<td>$AA10^-$</td>
<td>0.287935</td>
<td>0.022124</td>
<td>0.239534 0.336335</td>
</tr>
<tr>
<td>$AA50^-$</td>
<td>-0.08895</td>
<td>0.01867</td>
<td>-0.12963 -0.04827</td>
</tr>
<tr>
<td>$AA90^-$</td>
<td>-0.12685</td>
<td>0.023115</td>
<td>-0.17721 -0.07648</td>
</tr>
<tr>
<td>$AI^-$</td>
<td>0.414783</td>
<td>0.014987</td>
<td>0.382128 0.447437</td>
</tr>
</tbody>
</table>

### Table 7: Proportional ambiguity attitudes compared to US population

<table>
<thead>
<tr>
<th>Ambiguity Scenario</th>
<th>$AA10^+$</th>
<th>$AA50^+$</th>
<th>$AA90^+$</th>
<th>$AA10^-$</th>
<th>$AA50^-$</th>
<th>$AA90^-$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Averse (Kenyan sample)</td>
<td>18.8</td>
<td>65.2</td>
<td>71.0</td>
<td>67.4</td>
<td>22.5</td>
<td>37.7</td>
</tr>
<tr>
<td>Averse (US population)</td>
<td>18.5</td>
<td>52.4</td>
<td>57.7</td>
<td>33.6</td>
<td>9.4</td>
<td>14.5</td>
</tr>
<tr>
<td>Neutral (Kenyan sample)</td>
<td>11.6</td>
<td>6.5</td>
<td>5.8</td>
<td>7.2</td>
<td>9.4</td>
<td>14.5</td>
</tr>
<tr>
<td>Neutral (US population)</td>
<td>21.5</td>
<td>9.9</td>
<td>12.8</td>
<td>26.9</td>
<td>68.1</td>
<td>47.8</td>
</tr>
<tr>
<td>Seeking (Kenyan sample)</td>
<td>69.6</td>
<td>28.3</td>
<td>23.2</td>
<td>25.4</td>
<td>68.1</td>
<td>47.8</td>
</tr>
<tr>
<td>Seeking (US population)</td>
<td>60.0</td>
<td>37.7</td>
<td>29.5</td>
<td>39.6</td>
<td>60.0</td>
<td>39.6</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Our results show that for gains for moderate likelihoods, 65.2% are ambiguity averse, 6.5% ambiguity neutral and 28.3% ambiguity seeking. For high likelihood of winning 71% are ambiguity averse, 5.8% ambiguity neutral and 23.2% ambiguity seeking. For low likelihoods of winning 18.8% is ambiguity averse, 11.6% is neutral and 69.6% ambiguity-seeking. This pattern corresponds to the ambiguity attitudes found for gains in the U.S. population. However, our results show stronger ambiguity aversion and weaker ambiguity neutrality than found in the U.S. population. Interestingly, there is a difference in the ambiguity attitudes for moderate losses between Dimmock’s results and ours. Dimmock et al. (2015) find a more balanced distribution of neutral, seeking and averse behaviour, we find that most respondents are ambiguity-seeking for losses. Dimmock et al. do not have a high and low likelihood
scenario for losses so we cannot compare those. But it is clear that for the gain scenarios, our pattern of ambiguity attitudes is very close to the patterns described in the theory. Table 8 shows the distribution of sensitivity towards ambiguous situations or the perception of ambiguity. The third column indicates the findings for the U.S. population.

<table>
<thead>
<tr>
<th>A-insensitivity</th>
<th>Gain%</th>
<th>Loss%</th>
<th>Gain% US</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-insensitive</td>
<td>89.9</td>
<td>79.7</td>
<td>80.5</td>
</tr>
<tr>
<td>A-neutral</td>
<td>2.2</td>
<td>2.9</td>
<td>7.5</td>
</tr>
<tr>
<td>A-oversensitive</td>
<td>8.0</td>
<td>17.4</td>
<td>12.0</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 8: A-insensitivity

We find that 89.9% of our sample is a-insensitive and only 2.2% a-neutral. The remaining 8% is oversensitive to ambiguity. The results show the same pattern as found in the U.S. population, however our sample contains a higher percentage of a-insensitive individuals and a lower percentage of neutrality or oversensitivity. Dimmock et al did not estimate ambiguity insensitivity for losses, so we cannot compare our findings to theirs. Baillon and Bleichrodt (2015) found that a-insensitivity was stronger for losses than it is for gains. We do not find this. Table 6 shows that a-insensitivity for gains is slightly larger than that for losses.

The results suggest the same pattern as found in the main literature on ambiguity attitudes and as stated in our first hypothesis. Ambiguity attitudes of Kenyan farmers seem to differ for gains and losses and we find predominantly ambiguity aversion for moderate and likely gains and unlikely losses and ambiguity seeking behaviour for moderate losses, likely losses and unlikely gains. The confidence interval of Table 6 also shows that all measures are significantly different from 0, which rejects neutrality to ambiguous situations as the default behaviour and thus rejects Expected Utility theory. To test whether ambiguity attitudes differ for gains and losses. We test whether $AA_{50}^+ = AA_{50}^-$. We regress our ambiguity aversion on a dummy which is 1 for the loss scenario and 0 for the gain scenario and on our control variables. This is essentially a test of reference-dependence, meaning that subjects first evaluate the change in wealth to a specific reference point and then as being either a gain or a loss. The dummy has a very significant coefficient. Wald’s test gives $F=19.25$, which rejects the hypothesis of no reference dependence hypothesis at the 1% level ($p=0.0009$). This confirms that ambiguity aversion differs for gains and losses, which is also what Dimmock et al. (2015) and Baillon and Bleichrodt (2015) find. Based on the signs of our ambiguity aversion variables, it seems like there is a reflection effect, meaning that the ambiguity attitudes for losses are a mirror image of those found for gains. We test this with the hypothesis mean $AA_{50}^+ = -AA_{50}^-$. The null hypothesis, i.e. a reflection effect, cannot be rejected with $t=0.226$ and a p-value of 0.82. We cannot reject that ambiguity aversion for gains is reflected into ambiguity-seeking behaviour for losses. Dimmock et al. (2015) find the same result.
This might mean that the curvature of the probability weighting function is the same for gains and losses. We test for this hypothesis of $AI^+ = AI^-$, controlling for clustering effects. We find that the loss dummy is significant at the 1% level ($p=0.007$), which rejects the hypothesis that gains and losses are equally weighted. We find that our sample perceives higher ambiguity in the loss domain than in the gain domain, which is directly opposite to the prediction of Baillon and Bleichrodt (2015). Tests for linearity of the probability weighting function for both gains and losses, or whether $AI^+$ and $AI^-$ both equal zero are very significant. This is no surprise after looking at the confidence interval of Table 6. Our test-statistics confirm this and we reject neutrality for the weighting function for gains with $t=76.1$ and for losses with $t=99.8$. Both hypotheses are rejected at the 1% level with $p=0.000$. This is in line with the inverse-S function of underweighting high probabilities and overweighting low probabilities of Prospect Theory. Booij and van de Kuilen (2009) find that most studies report a measure of probability weighting of around 0.67, which is similar to the transformed estimate for a-insensitivity of Dimmock et al (2015). They measure a-insensitivity for gains at 0.320. A one-sided $t$-test on whether our estimate of a-insensitivity for gains of 0.517 is larger than Dimmock’s estimate of 0.320, yields a highly significant test-statistic with $p=0.000$. If we transform our measure to the same scale, i.e. calibrate to 1 for neutrality, we get 0.493 which is thus significantly lower than the average in the literature on probability weighting. This means that we find more insensitivity to likelihoods, resulting in a heavier inverse-S shape. We have therefore proven our second hypothesis, we find that our sample showcases stronger ambiguity generated insensitivity than found in other studies. A-insensitivity is linked to cognition and can decrease after experience or learning. Our sample has less experience with probabilities and has less education than the American population, which led us to this hypothesis.

The results of our first game have confirmed our first and second hypothesis. We find that Kenyan farmers showcase the same pattern of ambiguity attitudes as found in other studies, on for example the U.S. population. Kenyan farmers are on average ambiguity averse to moderate and highly likely gains and also to unlikely losses. They are ambiguity seeking for unlikely gains and moderate and highly likely losses. Compared with the study conducted on the U.S. population, we find relatively more a-insensitive individuals and also significantly higher a-insensitivity. Our results are in line with Prospect Theory, which is flexible in its incorporation of ambiguity attitudes parameters. Key assumptions of Prospect Theory have been found in our data: reference-dependence, reflection and probability weighting. Moreover, the data raises more doubts on whether the Multiple Prior models can explain the full pattern of ambiguity attitudes found in decision making. According to Baillon and Bleichrodt (2015), the $\alpha$-MaxMin Model is also a viable option for modelling decision-making under uncertainty. Besides the implausible assumption of EU under risk, the $\alpha$-MaxMin Model, cannot accommodate a-oversensitivity in its parameters (Baillon et al., 2016). It can only explain situations of a-insensitivity. However 8% of our sample showed oversensitivity to ambiguity generated likelihood in the gain domain.
and 17.4% in the loss domain. In contrast, Prospect Theory is able to include a-oversensitivity and is therefore more appealing for modelling decision making of Kenyan farmers.

4.2: Loss aversion
Table 9 presents the results of the loss aversion game for all three methods of estimation. Our first estimate of loss aversion assumes equal probability weighting for gains and losses and no diminishing sensitivity and is obtained by: \( \lambda_1 = \frac{G}{L} \), where G stands for the fixed gain of 150 KSh and L stands for the value of the latest choice lottery still accepted by the subject. If all questions are accepted, L=175, if all questions are rejected L≤50. If only question 1 is accepted and the rest rejected, then L=50. On average respondents showed loss aversive behaviour. The mean estimate is 2.18 and the median, which is the most common estimate used in the literature, is 2. It is important to note that 132 observations return to \( \lambda=3 \). Of this segment, 59 subjects rejected all games, resulting in a score of \( \lambda=3 \). Similarly, 36 subjects accepted all games and have an estimate of \( \lambda \leq 0.857 \).

Our second estimation of loss aversion assumes both diminishing sensitivity and probability weighting, based on the literature review. We take Abdellaoui’s estimate of probability weighting for gains and losses of \( \omega=0.86 \) and Booij and vande Kuilen’s estimate of diminishing sensitivity for gains \( \alpha=0.859 \) and losses \( \beta=0.826 \). Our estimate is derived by the following equation:

\[
\lambda_2 = 0.86 \left( \frac{G^{0.859}}{L^{0.826}} \right)
\]

Our third estimation of loss aversion has the same assumptions on probability weighting and diminishing sensitivity, but uses the data derived from the ambiguity game to estimate probability weighting. We did not derive any measures that allow us to estimate the parameters of diminishing sensitivity. Using the following equations, we can estimate \( \lambda_3 \), where \( \gamma \) is the parameter for pessimism captured by \( AA_{50}^+ \) for gains and \( AA_{50}^- \) for losses and \( \delta \) is the parameter for likelihood insensitivity captured by \( AI^+ \) and \( AI^- \).

\[
\omega(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1 - p)^\gamma}
\]

\[
\lambda_3 = \hat{\omega} \left( \frac{G^{0.859}}{L^{0.826}} \right)
\]

To avoid outliers we take the medians of the ambiguity attitudes, which gives us \( AI^+=0.515, AI^-=-0.435, AA_{50}^+=0.135 \) and \( AA_{50}^-=-0.12 \). We will have to transform our measures to make them in line with the parameters of probability weighting which are calibrated to 1, whereas our measures are 0 for neutrality. We therefore transform our measures to be 1 for neutrality. Again we take the medians and get \( \delta^+=0.865, \delta^-=1.12 \), reflecting pessimism in both domains and \( \gamma^+=0.485 \) and \( \gamma^-=-0.565 \), reflecting insensitivity for extreme likelihoods, stronger for gains than for losses. We take the mean estimates of
elevation and curvature and use those to calculate $\omega^+=0.463$ and $\omega^-=0.528$. This yields a probability weighting function of $0.463/0.528=0.877$ which lies very close to the average of 0.86 obtained in other studies. Unsurprisingly, the measures of loss aversion of our second and third estimation method are very similar.

$$\omega^+ = 0.463 \quad \text{and} \quad \omega^- = 0.528.$$ 

$$\frac{0.463}{0.528} = 0.877 \quad \text{which lies very close to the average of 0.86 obtained in other studies.}$$

Table 9: Three estimates of Loss aversion

<table>
<thead>
<tr>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\lambda_3$</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\leq 0.86$</td>
<td>$\leq 0.89$</td>
<td>$\leq 0.91$</td>
<td>28</td>
<td>10.1</td>
</tr>
<tr>
<td>Reject #6</td>
<td>1</td>
<td>1.01</td>
<td>1.03</td>
<td>12</td>
</tr>
<tr>
<td>Reject #5</td>
<td>1.2</td>
<td>1.18</td>
<td>1.20</td>
<td>22</td>
</tr>
<tr>
<td>Reject #4</td>
<td>1.5</td>
<td>1.42</td>
<td>1.44</td>
<td>40</td>
</tr>
<tr>
<td>Reject #3</td>
<td>2</td>
<td>1.8</td>
<td>1.83</td>
<td>42</td>
</tr>
<tr>
<td>Reject all</td>
<td>$\geq 3$</td>
<td>$\geq 2.51$</td>
<td>$\geq 2.56$</td>
<td>59</td>
</tr>
<tr>
<td>Mean</td>
<td>2.18</td>
<td>1.91</td>
<td>1.94</td>
<td>276</td>
</tr>
<tr>
<td>Median</td>
<td>2</td>
<td>1.8</td>
<td>1.83</td>
<td></td>
</tr>
</tbody>
</table>

Table 9 shows that imposing stricter assumptions on the parameters yields a lower estimate of loss aversion for $\lambda_2$ and $\lambda_3$. However, even if we take strong assumptions on the parameters for diminishing sensitivity and probabilistic weighting for gains and losses, we get a median between 1.8 and 1.83. All three estimates of loss aversion are significantly larger than 1 with $p$-values of 0.000, which confirms that loss aversion plays a role in decision making for our sample and supports the usage of PT. This confirms our third hypothesis that Kenyan farmers are on average loss averse.

This is a plausible result and similar to the estimate found in other studies. Booij and Kuilen (2009) find 1.58 and 1.87 (2007), whereas Gächter’s (2010) study yields 1.29. It should be noted that the method of estimation, parametric, non-parametric and assumptions on the estimates of diminishing sensitivity and probability weighting are important in determining the degree of loss aversion. The original estimate of Kahneman and Tversky (1992) is 2.25, which is often used as a focal point in modelling Prospect Theory. It is colloquially cited to state that losses are twice as strongly experienced as gains. Many recent studies, however, find values lower than 2 raising doubts on the original estimate. Depending on our parameterisation we get a median between 1.8 and 2. Our sample consists of subsistence farmers, who are on average poorer than Western counterparts and therefore the losses used in the experiment might have a greater impact on their wealth relative to Western respondents. It thus makes sense that our estimate of loss aversion is on the high end of recent literature. We find that an average farmer in Kenya experiences a loss almost twice as intense as a gain of the same size, which is in line with Prospect Theory. This has important consequences for decision making, particularly for financial goods such as insurance products.
4.3: Willingness-to-Pay and Analysis
The results of our WTP-game show that the mean WTP for the traditional insurance is 843 KSh with a standard error of 51 KSh, whereas the rebate type has a mean WTP of 900 KSh and a standard error of 66. The mean WTP of the rebate insurance is thus slightly higher, but this difference is not significant, which is also found when regressing WTP on our control variables and our rebate dummy variable. The coefficient of the rebate dummy has a positive sign but Wald’s test on the coefficient of the treatment (rebate) dummy gives F=0.19 with a p-value of 0.67, which does not confirm our hypothesis that WTP for the rebate type is significantly higher. Regressing WTP on either the gain or loss ambiguity attitudes and the rebate dummy and control variables also finds no significant difference between insurance type. The only significant effect we find is being currently insured, which has a significant negative effect on WTP (p=0.043). This could mean that there is an anchoring effect to the price they are used to pay for the insurance. The signs of the coefficients of the ambiguity attitudes are as expected with negative signs for the gain attitudes and positive signs for the loss attitudes. The negative signs imply that ambiguity averse and a-insensitive subjects are willing to pay less for index insurance because they respectively dislike and overweight (the probability of) basis risk. These findings provide evidence toward the validity of our third hypothesis, i.e. ambiguity aversion and a-insensitivity for gains are negatively correlated to WTP for both insurance designs due to basis risk. However, we only find significant evidence of this relation for a-insensitivity. Furthermore, we do not find any evidence to claim that this negative relation is less strong for the rebate type of insurance.

To analyse the relation between our behavioural attitudes and WTP and whether some of these traits can be linked to preferring one insurance type over the other, we include dummy variables. Of the respondents that participated in the gain ambiguity scenario, 47.8% falls into the relatively more loss averse category, 65.2% is ambiguity averse and 89.9% is a-insensitive. We regress WTP on a dummy variable for ambiguity aversion, loss aversion and a-insensitivity, the rebate dummy and our control variables. We find that our a-insensitivity dummy is significantly negative (p=0.085). This means that a-insensitive subjects have a significantly lower WTP for index insurance designs than subjects who are not a-insensitive. The coefficients for the loss averse and ambiguity averse dummies are negative but insignificant. Being insured also has a significant negative effect on WTP (p=0.059). The results can be found in column 1 of Table 10. Columns 2, 3 and 4 depict additional regressions, where in each regression one of the three behavioural dummies is interacted with the rebate dummy, while controlling for the other dummies as well as for our other control variables. We find that a-insensitivity and being insured remain significantly negative throughout the regressions. When interacting ambiguity aversion with the rebate dummy, which is shown in column 2, we find several significant effects. First of all we find that the coefficients of the ambiguity aversion and rebate dummies are significantly positive, with p=0.043 and p=0.086. This means that for the traditional insurance type, ambiguity averse individuals have a significantly higher WTP than those who are not ambiguity averse. Also, non-averse subjects have a significantly higher WTP for the rebate type. Secondly, the interaction is significantly negative
The interpretation is that the negative effect on WTP of begin ambiguity averse is significantly stronger when the rebate type of insurance is offered rather than the traditional insurance. Ambiguity averse subjects thus have a lower WTP for the rebate type insurance over the traditional type, than the non-ambiguity averse. This goes against our hypothesis and the ideas of Serfilippi et al. (2016) However, considering the fact that the rebate type of insurance essentially increases the degree of uncertainty, it is not unimaginable that ambiguity averse individuals dislike this type of insurance policy.

With regards to our fourth and fifth hypothesis, interacting loss aversion with the rebate yields no significant results. We do find that the coefficients of loss aversion flip from being negative for the traditional type to positive for the rebate type, but this is not significant. We expected that the loss averse subjects would have a higher WTP for the rebate insurance due to a framing effect. The stand-alone investment frame would change due to the removal of uncertainty of paying the premium towards a larger frame, where the possible loss would be larger. Loss averse individuals would want to ensure against this larger possible loss and thus have a higher WTP for the rebate type. If this were the case, we do not provide evidence to substantiate our fourth and fifth hypothesis. Further research is warranted to investigate how and if framing effects of index insurance design can alter the reference point assumed when making insurance purchasing decisions and how this relates to ambiguity attitudes and loss aversion. Interacting a-insensitivity with the rebate dummy also yields no significant findings.

Table 10: Results of OLS regressions of WTP

<table>
<thead>
<tr>
<th></th>
<th>(1) WTP</th>
<th>(2) WTP (Ambiguity Averse)</th>
<th>(3) WTP (Loss Averse)</th>
<th>(4) WTP (A-insensitivity)</th>
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</thead>
<tbody>
<tr>
<td>Ambiguity Averse</td>
<td>-21.82</td>
<td>212.9**</td>
<td>-21.32</td>
<td>-17.03</td>
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<tr>
<td></td>
<td>(106.3)</td>
<td>(93.97)</td>
<td>(107.7)</td>
<td>(108.1)</td>
</tr>
<tr>
<td>A-insensitivity</td>
<td>-322.0'</td>
<td>-299.2'</td>
<td>-319.3'</td>
<td>-225.1</td>
</tr>
<tr>
<td></td>
<td>(171.3)</td>
<td>(159.5)</td>
<td>(165.5)</td>
<td>(268.9)</td>
</tr>
<tr>
<td>Loss Averse</td>
<td>-33.03</td>
<td>-47.02</td>
<td>-44.61</td>
<td>-39.23</td>
</tr>
<tr>
<td></td>
<td>(118.7)</td>
<td>(108.3)</td>
<td>(119.8)</td>
<td>(111.2)</td>
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<td>Rebate</td>
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<td>443.3'</td>
<td>85.49</td>
<td>307.2</td>
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<td></td>
<td>(149.6)</td>
<td>(236.9)</td>
<td>(155.5)</td>
<td>(298.3)</td>
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<td>Age</td>
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<td>1.845</td>
<td>0.342</td>
<td>0.524</td>
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<td>(2.609)</td>
<td>(1.841)</td>
<td>(2.421)</td>
<td>(2.520)</td>
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<td>Education</td>
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<td>11.57</td>
<td>4.205</td>
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<td>(20.60)</td>
<td>(18.05)</td>
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<td>(93.11)</td>
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<td></td>
<td>(87.34)</td>
<td>(97.23)</td>
<td>(89.31)</td>
<td>(88.65)</td>
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<tr>
<td>Farmer group f.e.</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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</table>

Interaction effects

<table>
<thead>
<tr>
<th>Dummy×Rebate</th>
<th>-494.1**</th>
<th>21.71</th>
<th>-230.4</th>
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<tr>
<td></td>
<td>(218.0)</td>
<td>(129.4)</td>
<td>(360.4)</td>
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Constant

<table>
<thead>
<tr>
<th>937.6***</th>
<th>536.4**</th>
<th>942.7***</th>
<th>811.1**</th>
</tr>
</thead>
<tbody>
<tr>
<td>(233.9)</td>
<td>(198.8)</td>
<td>(218.8)</td>
<td>(292.5)</td>
</tr>
</tbody>
</table>

N 138 138 138 138
r² 0.106 0.149 0.106 0.110

Standard errors in parentheses clustered on the group level. * p < 0.10, ** p < 0.05, *** p < 0.01. Column 1 regresses WTP on the dummies for Ambiguity Aversion, Loss Aversion and A-insensitivity and other control variables. For column 2-4 the dummy which is interacted with the rebate dummy is in parentheses.
At first glance we find no significant difference between the two insurance types. Using dummies for specific behavioural attitudes suggests that a-insensitive individuals, who take up 90% of the sample, have a significantly lower WTP for both insurance types than those who are not a-insensitive. This confirms our hypothesis. Surprisingly, we find that the ambiguity averse individuals have a significantly lower WTP for the rebate type over the traditional insurance. This rejects our hypothesis that WTP would be higher for the rebate type and that this would be driven by ambiguity and loss attitudes.

5. Discussion
There are several limitations to our study. First of all, by splitting up our sample into 2 groups for the ambiguity game, the sample size was reduced drastically. For the regressions of WTP on our behaviour dummies we could only include the people that participated in the ambiguity game for gains (N=138). Of this group, half faced the traditional insurance and the other the rebate insurance type. This caused a reduction of the power of our analyses. We used random stratification at the group level, meaning that within every farmer group, people were randomly assigned which games to play. Even though we restricted the farmers from sharing information from one to another as much as possible, it is possible that subjects influenced each other slightly. This could lead to intra-group correlation, especially with respect to the WTP-game, where they were sitting close together. Even though we did not find any statistically worrying intra-class correlations, we did decide to cluster our standard errors at the farmer-group level. If this was redundant, the result would be the same as normal robust standard errors. This increase in the standard error, however, makes it harder to find any significance. This combination of reduced sample size and increased standard errors, made it difficult to confirm some of our hypotheses.

Thirdly, there are reasons to believe that not all farmers fully understood the ambiguity game. We investigated this with two check questions that measured consistency in the answers given. Out of 287 respondents, only 17 answered both questions correctly, 192 had at least one correct (the answer indifferent was right nor wrong), 48 had one incorrect and 15 responded both incorrectly. This raises doubts on the reliability of the data and whether the game might have been too abstract for good understanding. Removing all observations that had at least one question incorrect was not possible, as this would drastically reduce our sample size.

Fourthly, the source of uncertainty used is another limitation. Baillon et al. (2016, p 2) reviews that “several authors warned against the focus on artificial ambiguities, arguing for the importance of natural events”, among whom Ellsberg himself. Abdellaoui (2011) shows that ambiguity attitudes are dependent on the source of ambiguity and argues that artificial sources might induce different responses than those faced in reality. Baillon and Bleichrodt (2015) do not find this difference. Baillon et al. (2016) find no significant ambiguity aversion on a study on students while using a familiar source of uncertainty: changes on the stock market. Initially, we designed a game where we would take a natural source of uncertainty of something related to the weather. Then we came up with a design of 2 bottles of different
shapes filled with maize kernels. They could choose between the ambiguous option of e.g. bottle 1 weighs more than bottle 2 or a risky option of a winning chance of 50%. Matching probabilities and ambiguity attitudes would be derived from a point of indifference between the risky and ambiguous option, following the methodology of Baillon et al. (2016). While piloting we found that this caused great confusion to the farmers, especially when the ambiguous event with high likelihood occurred. This had two winning statements, for example you win if bottle 2 weighs less than bottle 1 or weighs the same amount. We therefore went back to a simpler artificial source of ambiguity with as much visualisation as possible, as described in this study. Unfortunately, the consistency questions reveal that understanding of the game was for some subjects difficult.

Similarly, to avoid confusion we decided to exclude upside basis risk from the WTP-game. Upside basis risk is the possibility of receiving a pay-out of the insurance while also experiencing a good harvest. If we would have included this, it is probable that ambiguity-seeking or optimistic individuals would have reacted more positively to this than ambiguity averse individuals. This would be an interesting topic for additional research.

Furthermore, there might have been quite some anchoring effects for the WTP-game. As explained in section 3.5, there might have been an anchoring effect from the March household survey WTP-game. Also 19.9% of our sample was insured at the time of our framed field experiment, which we found to significantly decrease WTP for both types of insurance, using the gain ambiguity attitudes. This implies that there was a strong anchoring effect. We tried to reduce both possible anchoring effects by setting a price range of which the lower boundary was the same as the highest possible price they could have anchored to (400 KSh) after the March survey. We found no anchoring effects for the March-session. However, the setting of the price range, might have caused some anchoring by itself. The results of our WTP-game should therefore not be interpreted as true demand, or actual prices they will pay for insurance.

Finally, in every game we endowed people with a participation fee. We did not want our participants to use their own money and possibly losing some of it. This could have led to an endowment effect, if subjects integrated their endowment and therefore considered it as a gain scenario. Other studies like Baillon and Bleichrodt (2015) find no significant differences between ambiguity attitudes for losses measured with real or hypothetical losses. Also, Etchart-Vincent and l’Haridon (2011) find that hypothetical versus real losses only differ in the gain domain. We therefore do not expect that our sample exhibited an endowment effect. Moreover, if they would have considered it as an eventual gain, we would not have found significant differences between the ambiguity attitudes for gains and losses.
6. Conclusion

This study confirms that there is much variety in how people respond to ambiguous situations. Confirming the main literature on ambiguity attitudes, we show that Kenyan subsistence farmers are on average ambiguity averse to moderate and highly likely gains and also to unlikely losses. They are ambiguity seeking for unlikely gains and moderate and highly likely losses. Moreover, they are significantly loss averse. We also confirm that Kenyan farmers are more a-insensitive than found in Western studies, which means that they are less able to discriminate between different likelihoods leading to perceiving them as probabilities of fifty-fifty. Our findings are in line with Prospect Theory, which is flexible in its incorporation of ambiguity attitudes parameters. Key assumptions of Prospect Theory have been found in our data: reference-dependence, reflection, probability weighting and loss aversion.

We expected to find that ambiguity aversion and a-insensitivity are negatively correlated to WTP for both index-insurance types due to basis risk. Our study confirms this relation, with only a-insensitivity having a significant negative effect on WTP. The widespread a-insensitivity, 90% of our sample falls into this category, implies that farmers in rural Kenya overweight the probability of not being paid out while buying insurance and experiencing a bad harvest. This is the probable cause of the significantly negative effect on WTP observed. Our study finds no significant difference between willingness-to-pay for the traditional index insurance and the rebate type. Also, we expected to find that loss aversion would be negatively correlated to the traditional index insurance and positively to the rebate type due to a framing effect. The coefficient does change from negative for the traditional type of insurance to positive for the rebate, but this is very insignificant. We do not find enough evidence to proof that loss aversion significantly affects WTP, or that this has to do with a framing effect due to removing the certainty effect, inducing farmers to assume a higher reference point when assessing the rebate insurance. Surprisingly, we find that that the negative effect on WTP of being ambiguity averse is significantly stronger for the rebate insurance than for the traditional insurance. This can be explained by the fact that the rebate type essentially increases ambiguity in its design and is therefore valued less by ambiguity averse people. Unfamiliarity of the new design could also play a role. Loosely put, pessimistic people dislike an insurance design with more uncertainty more than an insurance with less uncertainty.

This study contributes to a richer understanding of how farmers’ perceive and respond to index insurance designs. It shows that farmers’ perception of index insurance designs is rather negative due to a dislike of ambiguity and overweighting of the likelihood of basis risk. Insurance design should be better attuned to these dominant ambiguity attitudes. As long as the presence of basis risk cannot significantly be reduced or as long as farmers in rural Kenya remain strongly a-insensitive, uptake of index insurance is unlikely to grow. It is important that more research is done on alternative designs, including as well upside basis risk, that are impacted less negatively by ambiguity attitudes.
References


Appendix A: Figures

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<thead>
<tr>
<th>Lottery</th>
<th>Accept</th>
<th>Reject</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1 If the coin turns up heads, then you win 150 KSh. If the coin turns up tails, then you lose 50 KSh. Do you accept or reject to play this game?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>#2 If the coin turns up heads, then you win 150 KSh. If the coin turns up tails, then you lose 75 KSh. Do you accept or reject to play this game?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>#3 If the coin turns up heads, then you win 150 KSh. If the coin turns up tails, then you lose 100 KSh. Do you accept or reject to play this game?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>#4 If the coin turns up heads, then you win 150 KSh. If the coin turns up tails, then you lose 125 KSh. Do you accept or reject to play this game?</td>
<td></td>
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</tr>
<tr>
<td>#5 If the coin turns up heads, then you win 150 KSh. If the coin turns up tails, then you lose 150 KSh. Do you accept or reject to play this game?</td>
<td></td>
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</tr>
<tr>
<td>#6 If the coin turns up heads, then you win 150 KSh. If the coin turns up tails, then you lose 175 KSh. Do you accept or reject to play this game?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure A1: Starting scenario 1 of Ambiguity game (Gain)

Figure A2: The simple lottery choices

Figure A3: Example of lottery choice #1 as shown by the tablet
## Appendix B: Definitions

<table>
<thead>
<tr>
<th>Concept</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ambiguity Aversion</strong></td>
<td>The preference to bet on an option with known probabilities over an option with unknown probabilities. It is seen as a fixed trait of character and can also be interpreted as pessimism.</td>
</tr>
<tr>
<td><strong>Ambiguity-seeking</strong></td>
<td>The preference to bet on an option with unknown probabilities over an option with known probabilities. It is seen as a fixed trait of character and can also be interpreted as optimism.</td>
</tr>
<tr>
<td><strong>Ambiguity neutral</strong></td>
<td>Indifference between betting on an option with unknown probabilities over an option with known probabilities. Neutrality corresponds to the predictions of Expected Utility theory.</td>
</tr>
<tr>
<td><strong>A-insensitivity (AI&gt;0)</strong></td>
<td>The cognitive aspect of ambiguity. The inability to sufficiently discriminate between different levels of ambiguity, transforming likelihoods towards fifty-fifty. Also the perceived level of ambiguity. The higher a-insensitivity is, the less the subject can discriminate between likelihoods.</td>
</tr>
<tr>
<td><strong>A-oversensitivity (AI&lt;0)</strong></td>
<td>The inability to sufficiently discriminate between different levels of ambiguity, overweighting highly likely events and underweighting highly unlikely events. The opposite of a-insensitivity.</td>
</tr>
<tr>
<td><strong>A-neutrality (AI = 0)</strong></td>
<td>Perfect discrimination between different levels of ambiguity generated likelihoods. Neutrality corresponds to the predictions of Expected Utility thyory.</td>
</tr>
<tr>
<td><strong>Basis risk</strong></td>
<td>The imperfect correlation between the indemnity payments and the actual losses of the farmer. Downside basis risk means experiencing a loss, but not receiving a pay-out. Upside basis risk means receiving a pay-out while experiencing no loss. Basis risk is caused due to an invalid index.</td>
</tr>
<tr>
<td><strong>Risk aversion</strong></td>
<td>The notion that people are more sensitive to a loss than to a gain of the same magnitude.</td>
</tr>
<tr>
<td><strong>Matching probability</strong></td>
<td>The objective probability for which a subject is indifferent between the risky option and the ambiguous option. It is used to elicit subjects’ beliefs about the probability of an event occurring.</td>
</tr>
<tr>
<td><strong>Framed lab-in-the-field</strong></td>
<td>An experiment in the field with provided context in either the commodity task, or information set the subjects use.</td>
</tr>
</tbody>
</table>