Lotto lotteries – Decision making under uncertainty when payoffs are unknown[†]

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Abstract

This paper analyses decision making under uncertainty when uncertain situations can be described as a Lotto lottery. In a Lotto lottery, the probability of winning a prize is objectively known, but the size of the prize is unknown. This paper first proposes a theoretical framework to model preferences over Lotto lotteries as compound lotteries. The first stage determines whether a prize is obtained, while the second stage determines the size of the prize. Second, the paper empirically analyses human behaviour when uncertainty can be described as a Lotto lottery. I find evidence for a mild degree of uncertainty aversion, i.e., subjects prefer lotteries with known prizes over lotteries with unknown prizes, everything else being equal. Further analysis shows that a combination of risk and ambiguity preferences can explain the subjects' uncertainty aversion.

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Keywords: decision making, uncertainty, risk aversion, lotteries, ambiguity aversion, subjective expected utility, Anscombe-Aumann framework

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1 Introduction

Economists usually distinguish between two types of lotteries to analyse decision making under uncertainty: roulette lotteries and horse lotteries. In roulette lotteries, the payoffs and the probabilities for each of the payoffs are objectively known. In contrast, in horse lotteries, only the payoffs are known – but not the probabilities. Decision making under uncertainty which can be described by some type of roulette lottery is modelled using Expected Utility Theory (von Neumann and Morgenstern, 1944), while decisions under uncertainty for horse lotteries are modelled using Subjective Expected Utility Theory (Savage, 1954; Anscombe and Aumann, 1963).

Yet, many situations in everyday life do not correspond to either group; situations where the probabilities for payoffs are objectively known, but the exact payoff is not specified. The standard state lottery (Lotto), where participants are asked to guess 6 numbers out of 49, is one of the most prominent examples. In such lotteries, the probability of guessing all six number right can be easily calculated, but the prize depends on how many people participate in the lottery and how many of them guess the right numbers.

Besides the state lottery, there are many real-life examples for such lotteries. For example, when taking drugs, the probabilities of its side effects are fairly well-known in advance. Yet, the severities of the side effects are rather unknown (Budesco and Templin, 2008). Or, in most political elections, the relative proportion of votes for each party (or candidate) is fairly well-known in advance. However, quite often, the outcome of the election (e.g., the actual policy implemented) is rather unknown.[1]

The objective of this paper is to better understand decision making under uncertainty when uncertain situations can be represented by a Lotto lottery, i.e., where the probability of winning a prize is known, but not the size of the prize. Despite their relevance in many everyday life situations, there is little theoretical and empirical research about Lotto lotteries. This paper aims to fill this gap.

First, the paper provides a formal structure to model decision making if uncertainty can be described by a Lotto lottery. The model is inspired by the Anscombe and Aumann (1963) model of subjective expected utility theory. Preferences over Lotto lotteries are modelled using a two-stage compound lottery. The first stage involves a roulette lottery (with objective probabilities) over different states of the world, determining whether a payoff is obtained. The second stage consists of a horse lottery (with subjective probabilities), assigning subjective probabilities to the potential payoffs, given some state of the world is realised.

Second, the paper empirically analyses decision making when confronted with Lotto lotteries. Using a new experimental set-up, I examine a decision maker's attitude towards lotteries with unknown payoffs relative to lotteries with known payoffs. Consistent with prior empirical evidence I only find a mild degree of *uncertainty aversion*, i.e., subjects prefer roulette lotteries over Lotto lotteries, everything else being equal.

Then I examine the underlying source of the subjects' uncertainty aversion. The basic compound lottery model suggests that risk preferences should be sufficient to explain decision making in the presence of Lotto lotteries, and hence the subjects' uncertainty aversion. The empirical

[1] These examples abstract from any possible random or strategic interaction between lottery players or voters. More examples are presented and discussed in Du and Budescu (2005) and Budesco and Templin (2008).

results provide some support for this hypothesis. However, further analysis shows the importance of including ambiguity preferences (i.e., aversion to lotteries with unknown probabilities) to explain the subjects' behaviour when facing Lotto lotteries.

Despite their relevance, there is surprisingly little theoretical and experimental literature on preferences over Lotto lotteries. Schoemaker (1989) is the first to develop a framework similar to a Lotto lottery. Different from the concept of Lotto lotteries proposed in this paper, Schoemaker (1989) assumes that decision makers have objective information about the probabilities for each of the possible prizes. This compound lottery can therefore be reduced to a simple lottery, and be analysed using expected utility theory. Camerer and Weber (1992) discuss the situation when payoffs of lotteries are left unspecified, or ambiguous. They argue that decision makers will assign subjective probabilities for each of the possible outcomes (unless they are objectively given). They conclude that choices over Lotto lotteries should be perfectly explained by subjective expected utility, and hence risk preferences only. Yet, they do not provide a formal treatment of Lotto lotteries. Lotto lotteries also share some similarities with models that build on the concept of belief functions, developed by Dempster (1967) and Shafer (1976). The relation to this literature is reviewed in section 7. While very interesting from a theoretical point of view, these models are difficult to directly estimate.

The compound lottery model proposed in this paper offers such a framework. Essentially, it formalizes the ideas of Camerer and Weber (1992). Furthermore, it is shown that the model is – under certain conditions – equivalent to the Anscombe and Aumann (1963) model of subjective expected utility. Similar to Lotto lotteries, the Anscombe and Aumann (1963) framework consists of a compound lottery. Different from Lotto lotteries, however, Anscombe and Aumann (1963) attribute subjective probabilities over all possible states of the world, and objective probabilities for the lotteries played contingent on the state realized.

The empirical literature on human behaviour in situations that can be described as Lotto lotteries is also scarce. There are, however, some experimental studies in the psychology and management science literature that look at similar cases, albeit using different terms. Management science uses the term "imprecise outcomes" (Du and Budescu, 2005), and psychologists talk about "vague payoffs" (Gonzáles-Vallejo et al., 1996). This literature examines individual attitudes towards gambles with imprecise (or vague) payoffs, and also compares the difference between uncertain outcomes and uncertain probabilities on human decision making.

These studies present mixed evidence on attitudes towards gambles with uncertain outcomes. In his review, Onay et al. (2013) shows that these attitudes depend on the elicitation method, and whether the uncertain outcome involves gains or losses. While Budesco et al. (2002), Du and Budescu (2005), Budesco and Templin (2008) and Onay et al. (2013) find that the majority of subjects are uncertainty seeking when facing uncertain gains, Gonzáles-Vallejo et al. (1996) and Ho et al. (2002) show that subjects are uncertainty averse, on average. Most of these studies also show that there is a positive relation between a decision makers' attitude towards imprecise outcomes and attitude towards imprecise probabilities (i.e., ambiguity preferences). Yet, as they point out, subjects tend to display a "higher concern for precision of the outcomes than that of the probabilities" (Kuhn et al., 1999; Budesco et al., 2002).[2]

While these empirical studies allow for a first understanding of decision making under uncertainty if payoffs are unknown, they suffer from a number of shortcomings. Most allow only for a

[2] Other important studies include Kuhn and Budescu (1996) and Ho et al. (2001).

binary differentiation between uncertainty averse and uncertainty seeking preferences. The novel uncertainty preference tasks introduced in this study allow for a much finer measurement of the subjects' uncertainty aversion. Furthermore, the analyses of the existing literature are mostly non-parametric, and not benchmarked against any economic model of decision making under uncertainty. Most of all, it is not clear whether the pattern of decision making documented in these studies can be explained by the economic preference parameters of risk aversion, as suggested by Schoemaker (1989) and Camerer and Weber (1992), ambiguity aversion, or whether uncertainty preferences can be traced back to both preference parameters.

The remainder of this paper is organized as follows. The next section proposes a compound lottery model to formalise the concept of Lotto lotteries. Section 3 then introduces the concept of uncertainty aversion as a preference for lotteries with known payoffs over lotteries with unknown payoffs, everything else being equal. Section 4 presents the experimental design. The results of the experimental sessions are the presented in section 5. Section 6 shows that preferences over Lotto lotteries can be best explained by a combination of risk and ambiguity preferences. Finally, section 7 discusses the related decision-theoretic literature. Section 8 offers some concluding remarks.

2 Lotto lotteries

This section formally introduces the concept of Lotto lotteries. Section 2.1 presents a stylized example of a Lotto lottery. Section 2.2 then shows that Lotto lotteries can be considered as compound lotteries. Building on this framework, section 2.3 presents a formal model of decision making under the uncertainty of Lotto lotteries.

2.1 Introductory example

Suppose a decision maker has the choice between drawing a ball from one of two urns, urn F and urn G. Both urns contain two balls, one white ball and one coloured ball. The coloured ball can be either red or yellow. If a red ball is drawn, the decision maker obtains a payoff of 1; if a yellow ball is drawn, the decision maker obtains a payoff of 2. There is no prize if the ball drawn is white. Put differently, the probability of receiving a prize is known (a probability of 50%), but the actual prize is not known. All that is known is that the payoff may be 1 or 2.

Table 1: Lotto lotteries

Type of ball	Probability	Colour	Payoff x
white	0.5	white	0
coloured	0.5	red	1
		yellow	2

Standard expected utility and subjective expected utility cannot model preferences over the two gambles, since they require an unambiguous mapping from outcomes of the gambles into payoffs (either utils, or monetary payoffs together with a utility function). For example, in expected utility theory, the set of outcomes would be $\{0, 1, 2\}$, but the probability for each of the outcomes is not known (only $p(x = 0) = 0.5$).

Nevertheless, if drawing a ball from urn F is strictly preferred to drawing a ball from urn G, it is natural to conclude that the decision maker believes that the coloured ball in urn F is yellow, and that the coloured ball in urn G is red.

2.2 Lotto lotteries as compound lotteries

It is possible to view Lotto lotteries as compound lotteries. The first lottery determines whether a prize is drawn or not, whose probabilities are objectively given. The second lottery then determines the amount of the prize. Schoemaker (1989) assumes that the probability distribution over the outcomes (i.e., the colour of the balls) is objectively known. Then it is possible to derive a reduced lottery, and apply expected utility to the resulting roulette lottery. Yet, in a typical Lotto lottery, there is no objectively given probability distributions over prizes.

An alternative is to leave the probability distribution over the prizes in the second stage unspecified. Then the decision maker's preferences over Lotto lotteries can be modelled using some subjective probability distribution over the prizes. Again, this allows to derive a reduced lottery, and apply subjective expected utility to the lottery.[3]

Example as compound lottery. In the example, there are 2 possible scenarios for each urn: either the coloured ball is red or yellow. However, the decision maker does not know which scenario corresponds to the true scenario. Since there is no objective information on probabilities for each of the scenarios for each of the urns, the decision maker might attribute subjective probability distributions μ to each of them:

$$\text{coloured ball in urn F} = \begin{cases} yellow(x^F = 2) & \text{with probability } \mu^F \\ red(x^F = 1) & \text{with probability } 1 - \mu^F \end{cases}$$

$$\text{coloured ball in urn G} = \begin{cases} yellow(x^G = 2) & \text{with probability } \mu^G \\ red(x^G = 1) & \text{with probability } 1 - \mu^G \end{cases}$$

The preference of drawing a ball from F or G then depends on the subjective probabilities μ^F and μ^G. It is natural to assume that the decision maker weighs the payoffs with their subjective probability, i.e., he calculates the payoff of the resulting compound lottery. In this case, the (subjective) expected utilities of gambles F and G are:

$$\begin{aligned} U(F) &= 0.5\left(u(2)\mu^F + u(1)(1-\mu^F)\right) + 0.5 \cdot u(0) \\ U(G) &= 0.5\left(u(2)\mu^G + u(1)(1-\mu^G)\right) + 0.5 \cdot u(0) \end{aligned}$$

From this it follows:

[3] An alternative is to put forward a model of decision making for Lotto lotteries by replacing the assumption of objectively known payoffs by some subjective payoffs. Essentially it is always possible to rationalize the choices between two Lotto lotteries by assuming some subjective valuation for the possible outcomes. This would, however, constitute a departure from existing expected utility theories.

$$\begin{aligned} F &\succ G \Leftrightarrow \\ U(F) &> U(G) \Leftrightarrow \\ (u(2)-u(1))\,\mu^F &> (u(2)-u(1))\,\mu^G \end{aligned}$$

As long as $u(2) > u(1)$, it follows $\mu^F > \mu^G$. Hence, for any increasing utility function over payoffs, the decision maker will select the urn where she attributes a probability of drawing a yellow ball (that entitles her to a payoff of 2) is higher.

2.3 Compound lottery model

Assume there is a finite set $\mathcal{S}$ of s states of the world. Assume that the probabilities for each state of the world to occur is objectively given, such that

$$\begin{aligned} \sum_{s\in\mathcal{S}} p_s &= 1 \\ p_s &\geq 0 \quad \forall s \end{aligned}$$

In this model, the each state has an objective probability. Put differently, there is a roulette lottery over all possible states. States are observable ex-post.

Furthermore, there is a set of $\mathcal{X}$ of x possible payoffs. This is final payoff for the decision maker. Then define a set $\mathcal{C}$ of c possible scenarios. Mathematically, scenarios are functions from states into payoffs, $\mathcal{C} : \mathcal{S} \to \mathcal{X}$. Put differently, a scenario specifies for each state $s \in \mathcal{S}$ a payoff $x \in \mathcal{X}$. Finally, a bet B is a list of subjective probabilities for each of the scenarios, such that

$$\begin{aligned} \sum_{c\in\mathcal{C}} \mu_c(B) &= 1 \\ \mu_c(B) &\geq 0 \quad \forall c \end{aligned}$$

Then preferences $\succ$ over any two bets B and B' can then be represented by a utility function:

$$B \succ B' \Leftrightarrow U(B) > U(B') \Leftrightarrow \sum_{s\in\mathcal{S}} p_s \left(\sum_{c\in\mathcal{C}} \mu_c(B)u(x_{c,s})\right) > \sum_{s\in\mathcal{S}} p_s \left(\sum_{c\in\mathcal{C}} \mu_c(B)u(x_{c,s})\right) \qquad (1)$$

for some $\mu_c(B)$ and $\mu_c(B')$. Note that $x_{c,s}$ denotes the payoff of the bet in state s under scenario c. $u(\cdot)$ is a standard (Bernoulli) utility function over sure payoffs.

While this paper does not provide an axiomatic proof of the utility representation of Lotto lotteries, appendix A shows that the model can be transformed in the Anscombe and Aumann (1963) model of subjective expected utility.

Example, revisited. In the example, the state of the world is the result of the draw, i.e., $\mathcal{S} = \{coloured, white\}$. The probability for each state of the world to occur is $p_c = p_w = 0.5$.

The set of payoffs is $\mathcal{X} = \{0, 1, 2\}$. The set $\mathcal{C}$ of c possible scenarios is given by

$$\begin{aligned} c_{yellow} &= (2, 0) \\ c_{red} &= (1, 0) \end{aligned}$$

In this notation, the first number gives the payoff if $s = coloured$, and the second number gives the payoff in case of $s = white$. Finally, there are two bets, F and G with subjective probabilities μ^F and μ^G for the first scenario. Hence, $F \succ G$ if and only if $\mu^F > \mu^G$ (for the calculation see section 2.1 above).

■

A few aspects are worth discussing. First, the term “states of the world” differs from other notions in the literature. In this model, a “state of the world” corresponds to the outcome of the first-stage lottery. It should not be confused with the prize or the colour of the ball drawn. In the example, “red” is not a state of the world. In this case, the state of the world would be “coloured”.

Second, the example is perfectly symmetric, i.e., the possible scenarios are identical for both urns. If they are not symmetric (such as a third possible prize for one of the bets), there are two possible ways to extend the model. One option is to impose some (subjective) null-probability on scenarios that are not possible for a certain bet. Alternatively, it is possible to specify a set of scenarios for each bet separately, i.e., $\mathcal{C}^F$ and $\mathcal{C}^G$.

Finally, the state of the world is always observable ex-post. The true scenario is, however, not always fully revealed – it is only revealed for the realized state of the world.

3 Uncertainty aversion

The stylized example and the compound lottery model present the general case where a decision maker has the choice between two Lotto lotteries. This section presents a special case where decision makers have the choice between a Lotto lottery and a roulette lottery. The conjecture is that subjects prefer lotteries with known prizes over lotteries with unknown prizes, everything else being equal.

3.1 Lotto lotteries versus roulette lotteries

Suppose a decision maker has the choice between drawing one ball from one of two urns, urn F and urn G. Both urns contain two balls, a white ball and a coloured ball. The coloured ball can be either blue, red or yellow. If a red ball is drawn the decision maker receives payoff of 1, if a blue ball is drawn he obtains a payoff of 2, and if a yellow ball is drawn he obtains a payoff of 3. He doesn't receive any prize if the ball is white. The decision maker knows that the coloured ball in urn F is blue; but all he knows about the coloured ball in urn G is that it is either red or yellow.

Table 2: Urn F

Type of ball	Probability	Colour	Payoff x
white	0.5	white	0
coloured	0.5	blue	2

Table 3: Urn G

Type of ball	Probability	Colour	Payoff x
white	0.5	white	0
coloured	0.5	red	1
		yellow	3

In this example, urn F is a roulette lottery, and it can be valued using expected utility. In contrast, urn G is a Lotto lottery, which can be analyzed using compound lottery model introduced in the last section. This requires attributing some subjective probabilities for the likelihoods of the coloured ball in urn G to be either red or yellow.

An expected choice in this thought experiment is to prefer urn F over urn G, i.e., a preference of the roulette lottery over the Lotto lottery. In the remainder of this paper, such a choice pattern is called *uncertainty aversion.*

3.2 Explaining uncertainty aversion

Although uncertainty aversion may be an expected choice pattern in such situations, it can be rationalized by four different theoretical explanations: (1) risk aversion, (2) non-symmetric subjective probabilities, (3) ambiguity aversion, and (4) non-symmetric ambiguity.

1. Risk aversion: If the decision maker has symmetric subjective probabilities for the high and the low prize in the Lotto lottery, risk aversion implies a higher (subjective) expected utility of the roulette lottery relative to the Lotto lottery.

2. Non-symmetric subjective probabilities: If the decision maker attributes a higher subjective probability for the low prize relative to the high prize in the Lotto lottery, the (subjective) expected utility of the roulette lottery is higher than the Lotto lottery, even for a risk-neutral decision maker.

3. Ambiguity aversion: If the decision maker is not sure about the (subjective) probabilities for the high and low prize in the Lotto lottery, he might consider a symmetric range of probabilities possible (ambiguity). If the decision maker is ambiguity averse, he will prefer the roulette lottery over the Lotto lottery, even if the decision maker is risk neutral.

4. Non-symmetric ambiguity: If the decision maker attributes a higher probability range for the low prize than for the high prize, he will prefer the roulette lottery over the Lotto lottery, even if he is risk and ambiguity neutral.

For simple numerical examples of the four explanations, see appendix B. While the risk explanations (1) and (2) can be captured by the compound lottery model presented in section 2, it cannot explain the ambiguity-based explanations (3) and (4).

The empirical part of the paper analyses which of these four explanations are supported by the data. To allow ambiguity preferences to explain the subjects' behaviour, the compound lottery model has to be extended to include ambiguity as well.

4 Experimental design

4.1 Research design

The objective of the empirical part of the paper is to obtain a better understanding of decision making under uncertainty when uncertainty can be described as a Lotto lottery.

In a first step, I measure the subjects' uncertainty aversion, i.e., their aversion to lotteries with unknown payoffs (Lotto lotteries) relative to comparable lotteries with known payoffs (roulette lotteries). The conjecture is that subjects prefer roulette lotteries over Lotto lotteries, i.e., a preference of known payoffs over uncertain payoffs. Section 4.2 presents two decision tasks designed to measure the subjects' uncertainty aversion.

In the second step, I aim at explaining the subjects' uncertainty aversion. As shown in section 3.2, there are various possible explanations for subjects to prefer roulette lotteries over Lotto lotteries. While the compound lottery model presented in section 2.2 suggests that uncertainty aversion can be explained by risk aversion alone, the discussion in section 3.2 shows that ambiguity aversion might also play an important role to explain uncertainty aversion. The main analysis therefore examines whether uncertainty aversion can be by risk aversion, ambiguity aversion, or both. The choice tasks to measure risk and ambiguity preferences are presented in section 4.3. All tasks are reproduced in appendix C.

4.2 Measuring uncertainty aversion

There are potentially many possibilities to design decision tasks to measure a subject's aversion to uncertain outcomes, i.e., uncertainty aversion. The two tasks used in this study directly build on the example presented in section 3 to measure uncertainty aversion. The idea of both tasks is to offer subjects the choice between a Lotto lottery and a sequence of monotonically changing roulette lotteries with different expected values.

Uncertainty task 1 measures uncertainty preferences by eliciting an uncertainty equivalent to a Lotto lottery. The task presents subjects with a decision table of 11 choices between a Lotto lottery and a roulette lottery. The Lotto lottery offers a prize with a probability of 50%, but actual size of the prize is unknown; it can be either 0 or 10 points. The Lotto lottery is identical in all 11 situations. The roulette lottery also offers prizes with a probability of 50%. Different from the Lotto lottery, the prizes are known and increasing from situation to situation. The first situation offers a prize of 0 points, the second a prize of 1 point, and so on up to a prize of 10 points.

In the first scenario, subjects are expected to prefer the Lotto lottery over the roulette lottery since, at worst, both lotteries are identical (offering an expected payoff of 0 points). As the roulette lottery is getting more attractive, subjects are expected to switch to the roulette lottery at some point. The earlier they switch, the more they are uncertainty averse.

The lotteries are implemented using two boxes filled with balls of different colours.[4] Box I (the roulette lottery) contains 10 white balls (no payoff) and 10 black balls (with increasing payoffs from 0 to 10 points). Box J (the Lotto lottery) also contains 10 white balls (no payoff) and 10 coloured balls (which can be either all blue or all yellow), leading to a payoff of either 0 or 10 points, depending on the colour.

Uncertainty task 2 is a simplified version of uncertainty task 1, dropping the white balls from both boxes. Essentially, this task offers subjects a sequence of choices between two options. Option A offers a sure payoff, increasing from 0 points to 10 points. Option B is identical in each situation, offering a payoff that can be either 0 points or 10 points.

Similar to uncertainty task 1, subjects are expected to prefer option B (with uncertain payoff) in the first situation over option A (a sure payoff of 0 points). However, option A is getting more attractive from situation to situation, such that subjects are expected to switch to option A at some point. The earlier they switch, the more they are uncertain averse.

When measuring uncertainty aversion, and – more important – when trying to explain the subjects' uncertainty aversion, it is important to rule out the possibility that subjects have asymmetric subjective probabilities for the prizes, or asymmetric subjective probability ranges for the prizes in Lotto lotteries, see explanations (2) and (4) in section 3.1. Given the perfect symmetry of the Lotto lottery, it is a priori not clear why a decision maker would have such beliefs. One reason might be that the decision maker does not trust the experimenter (to save on budget), thereby increasing the subjective probability/probability ranges for a low prize (Chow and Sarin, 2002; Charness et al., 2013). To avoid such non-symmetric beliefs, participants were therefore asked to select the colour of the winning ball of the uncertain option (box J and option B) beforehand.

Note that the Lotto lotteries in both tasks correspond to the stylized Lotto lottery presented in the examples with a binary prize. Yet, the more general notion of Lotto lotteries leaves the prize completely unspecified. Section 6.3 therefore uses an alternative measure of uncertainty aversion, allowing for a complete (continuous) range of possible prizes.

4.3 Risk and ambiguity preferences

To measure risk and ambiguity preferences, this study uses standard choice lists taken from the literature. Similar to the uncertainty tasks, the lotteries are presented in the form of two-colour boxes.

Risk task 1 measures risk preferences by eliciting an uncertainty equivalent for a sequence of roulette lotteries. The task, which is a simplified version of the Holt and Laury (2002) design, is taken from decision sheet B of Chakravarty and Roy (2009). In this task, subjects are presented a decision table with 10 choices between a low-risk and a high-risk lottery. As the task proceeds from situation to situation, the low-risk lottery remains identical while the expected payoff of the high-risk lottery increases monotonically. The point at which subjects switch from the low-risk lottery to the high-risk lottery reveals information on the subjects' risk preferences.

[4] To allow for a better understanding of the tasks, this paper follows Dimmock et al. (2016) and uses in the experiments the term "box" instead of "urn" usually used in the economics literature.

Risk task 2 determines risk preferences by eliciting a certainty equivalent for a roulette lottery. The task is adapted from task 5 of Vieider (2018). In this task, subjects are presented a decision table with 14 choices between a roulette lottery and a safe payment. As the task proceeds, the lottery remains identical while the safe payment increases monotonically. The point at which subjects switch from the lottery to the safe payment again reveals the subjects' risk preferences.

Ambiguity task 1 determines ambiguity preferences by eliciting a matching probability for an ambiguous lottery. The task extents the Ellsberg (1961) thought experiment to different situations, and is taken from Cavatorta and Schröder (2019). The task involves 11 sequential decisions between a risky lottery and an ambiguous lottery. The expected payoff of the lottery increases from one situation to the next. This change is induced by increasing the probability of winning some prize, while leaving the potential prize constant. In contrast, the composition and payoff structure of the ambiguous lottery is identical in all 11 situations, offering a prize with unknown probability. The point at which subjects switch from preferring the ambiguous lottery to the risky lottery reveals their ambiguity preferences. As Dimmock et al. (2015) show, this design allows measuring ambiguity preferences independent of the subject's utility function, and thus risk preferences.

Ambiguity task 2 is a slight variant of ambiguity task 1, also determining ambiguity preferences by eliciting a matching probability for an ambiguous lottery. Different from ambiguity task 1, task 2 consists of 14 situations, and thus has a finer grid to measure preferences. Furthermore, the probability of winning a prize in the ambiguous lottery can be either 0% or 100% (instead of allowing for any probability).

In both ambiguity preference tasks, participants were asked to select the colour of the winning ball in the ambiguous box, similar to the uncertainty tasks. This procedure ensures that participants had symmetric beliefs about the composition of the ambiguous box.

4.4 Experimental procedure and participants

The experimental sessions took place in March 2019 at the ExpressLab at Royal Holloway, University of London. The laboratory sessions were implemented in z-tree (Fischbacher, 2007). 93 subjects participated at the study, most of them students of Royal Holloway, University of London. The subjects were recruited via electronic mail. The sample contains 47 (51%) male and 46 (49%) female subjects, with an average age of about 21 years.

The sessions started with the incentivized tasks measuring risk preferences, followed by the tasks to measure ambiguity and uncertainty preferences. In a second round of experiments (see section 6.3) the sequence of tasks was reversed, but no order effects were observed.

The payment modality of the incentivized tasks to measure uncertainty, risk and ambiguity preferences was common knowledge. Subjects were informed that one situation of each task would be randomly selected by the computer at the end of the session. If the subject's choice implied a draw from a box, the computer would randomly draw one ball. This procedure ensures that subjects state their true preferences.[5] Earnings from the tasks were calculated in terms of points, and then converted at a rate of 5:1 into GBP. On average, subjects earned GBP 11,

[5] Bade (2015) discusses some problems with this random incentive mechanism when subjects are ambiguity averse. Yet, to my knowledge, the random incentive mechanism remains the best incentive scheme to measure economic preferences and are commonplace in laboratory and field studies.

Table 4: Descriptive statistics of uncertainty preference tasks

Panel A: Non-parametric uncertainty aversion measure

	Observations	Mean	Standard deviation	Lowest	Highest
Uncertainty task 1	93	0.503	0.182	0.00	0.95
Uncertainty task 2	93	0.510	0.147	0.15	0.95
Combined uncertainty measure	93	0.507	0.127	0.20	0.90

Panel B: Correlation statistics

	Uncertainty task 1	Uncertainty task 2	Combined uncertainty measure
Uncertainty task 1		0.282***	0.792***
Uncertainty task 2	0.182*		0.768***
Combined uncertainty measure	0.823***	0.708***	

The table summarizes the results of the two uncertainty preference tasks. Panel A reports the non-parametric uncertainty aversion preference measures derived from the switching points. Significance of the difference to 0.5 is estimated using a *t*-test. Panel B reports the correlation statistics between the uncertainty preference measures. The lower part of the panel presents the Pearson correlation, the upper part the Spearman correlation. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. For a detailed description of the preference measures, see section 4.2 and appendices C and D.

which includes a fixed show-up fee of GBP 2.[6] Earnings were paid in private at the end of the sessions.

5 Experimental results

5.1 Uncertainty aversion

Table 4 presents the results of the uncertainty preference tasks. The standard choice pattern in binary choice lists is a threshold strategy. Since the relative attractiveness of one option changes monotonically as the list proceeds, subjects tend to prefer one option over the other up to a switching point. In both uncertainty tasks, the natural choice is to first select the Lotto lottery with uncertain payoffs, and then switching to the roulette lottery (uncertainty task 1) or the safe payment (uncertainty task 2). However, some subjects switch more than once – a behaviour that is difficult to reconcile with rational choice. There are 9 multiple switchers in the uncertainty task 1 (10% of the sample) and 7 multiple switchers in the uncertainty task 2 (8%).[7] In case a subject has multiple switching points, I follow Falk et al. (2016) and define a subject's switching point as her average switching point.

The switching point indicates a subject's indifference between the two options. This allows constructing a non-parametric measure of uncertainty aversion by linearly mapping the indifference points into an interval between 0 and 1. A value of 0 corresponds to extreme uncertainty seeking preferences, while a number of 1 means extreme uncertainty aversion. A value of 0.5

[6]Since the sessions lasted for about 60 minutes, the payoffs are substantial. The lowest payment was GBP 4, the highest payment GBP 16.

[7]Such a fraction is in line with other studies using binary choice lists, e.g., Holt and Laury (2002).

implies uncertainty neutrality (for more details, see appendix D). To reduce the impact of potential measurement errors, I also derive a synthetic measure of uncertainty aversion, calculated as the average uncertainty aversion measure obtained from both tasks.

Panel A shows that subjects are slightly uncertainty averse (>0.5) in both tasks, on average. Using a t-test, these averages are however not statistically different from 0.5. The finding of uncertainty neutrality is in line with the inconclusive results in the experimental psychology literature, which documents evidence for both uncertainty averse and seeking behaviour in the gain domain (see the introduction). Combining the two tasks reduces the variance of the uncertainty aversion measure significantly, suggesting that the synthetic measure allows correcting for outliers caused by measurement errors. In the remainder of the analysis, the paper thus predominantly relies on the combined measure of uncertainty aversion (baseline). Since uncertainty task 2 has fewer multiple switchers (which can be interpreted that the task is easier to understand) and a lower variance than uncertainty task 1, I also use this single measure of uncertainty aversion as robustness.

Panel B reports the correlation statistics between the various measures of uncertainty preferences. All measures are significantly related to each other, especially when using the Spearman (1904) correlation coefficient as measure of association.

5.2 Risk and ambiguity aversion

Table 5 presents the results from the risk preference tasks. Similar to the uncertainty tasks, a large majority of subjects exhibits a threshold strategy. In risk task 1, the standard choice is to first prefer the low-risk lottery, before switching to the high-risk lottery at some point. In this task, 11 subjects (12%) have multiple switching points. In risk task 2, the natural pattern is to first select the risky lottery and then switching to the safe payment. Again, there are few multiple switchers in task 2, accounting for 9 subjects (10%). As before, the switching point for these subjects is defined by computing their average switching point.

Similar to the uncertainty tasks, the switching points allow deriving non-parametric measures of risk aversion (see appendix D), where a value of 1 corresponds to extreme risk aversion, a number of 0 means extreme risk seeking preferences, and a value of 0.5 implies risk neutrality. Averaging the risk aversion measures obtained from both tasks gives a synthetic measure of risk aversion.

Panel A shows that subjects are, on average, risk averse (>0.5) in both tasks. The difference to 0.5 is highly significant using on a t-test (p-value < 0.01). Combining the two tasks considerably reduces the variance of the risk aversion measure, which I interpret as evidence that the synthetic measure allows for correcting of outliers. In the remainder of the analysis, the paper thus uses mostly the combined measure of risk aversion (baseline). Since risk task 2 has fewer multiple switchers, I also use this measure of risk aversion as robustness.

Using the switching points, it is possible to estimate the subject's coefficient of relative risk aversion. Panel B of table 5 presents the estimated coefficients of relative risk aversion (CRRA), where a positive value corresponds to risk aversion. The results are similar to those of the non-parametric risk aversion measure. While the average CRRA of task 1 is significantly positive, the average CRRA of task 2 is not. Finally, panels C and D report the correlation statistics between the various measures of risk preferences. Interestingly, the risk aversion measures obtained from

Table 5: Descriptive statistics of risk preference tasks

Panel A: Non-parametric risk aversion measure

	Observations	Mean	Standard deviation	Lowest	Highest
Risk task 1	93	0.548^{***}	0.129	0.20	0.95
Risk task 2	93	0.549^{***}	0.146	0.05	0.95
Combined risk measure	93	0.549^{***}	0.102	0.25	0.95

Panel B: Coefficient of relative risk aversion (γ)

	Observations	Mean	Standard deviation	Lowest	Highest
Risk task 1	93	0.089^{**}	0.364	-1.06	0.93
Risk task 2	93	-0.071	1.364	-12.51	0.77
Combined risk measure	93	0.009	0.719	-6.34	0.85

Panel C: Correlation statistics – non-parametric measure

	Risk task 1	Risk task 2	Combined risk measure
Risk task 1		0.032	0.689^{***}
Risk task 2	0.083		0.676^{***}
Combined risk measure	0.700^{***}	0.773^{***}	

Panel D: Correlation statistics – coefficient of relative risk aversion

	Risk task 1	Risk task 2	Combined risk measure
Risk task 1		0.032	0.741^{***}
Risk task 2	0.077		0.617^{***}
Combined risk measure	0.326^{***}	0.968^{***}	

The table summarizes the results of the two risk preference tasks. Panel A reports the non-parametric risk aversion preference measures derived from the switching points. Significance of the difference to 0.5 is estimated using a t-test. Panel B reports the estimated coefficients of relative risk aversion (γ) implied by the switching points. Panels C and D report the correlation statistics between the risk aversion measures. The lower part of the panels presents the Pearson correlation, the upper part the Spearman correlation. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. For a detailed description of the risk aversion measures, see section 4.3 and appendices C and D.

Table 6: Descriptive statistics of ambiguity preference tasks

Panel A: Ambiguity aversion parameter (α)

	Observations	Mean	Standard deviation	Lowest	Highest
Ambiguity task 1	93	0.532^{***}	0.083	0.25	0.65
Ambiguity task 2	93	0.535^{***}	0.091	0.33	0.85
Combined ambiguity measure	93	0.534^{***}	0.064	0.36	0.70

Panel B: Correlation statistics

	Ambiguity task 1	Ambiguity task 2	Combined ambiguity measure
Ambiguity task 1		0.088	0.706^{***}
Ambiguity task 2	0.069		0.711^{***}
Combined ambiguity measure	0.702^{***}	0.759^{***}	

The table summarizes the results of the two ambiguity preference tasks. Panel A reports the ambiguity preference parameters (α) derived from the switching points. Significance of the difference to 0.5 is estimated using a t-test. Panel B reports the correlation statistics between the ambiguity preference parameters. The lower part of the panel presents the Pearson correlation, the upper part the Spearman correlation. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. For a detailed description of the ambiguity preference measures, see section 4.3 and appendices C and D.

both two tasks are not significantly related to each other. This might indicate some measurement error due to random switching points (Vieider, 2018).

Table 6 presents the results of the ambiguity preference tasks. Similar to the previous tasks, most subjects adopt a threshold strategy with a single switching point between the two options. 10 subjects (11%) have multiple switches in ambiguity task 1, while 13 subjects (14%) have multiple switches in ambiguity task 2.

Following Dimmock et al. (2015), I derive the subject's matching probability (or risk equivalent) from the switching points. This matching probably m is defined as the probability at which a subject is indifferent between a risky and the ambiguous lottery. Using this matching probability, I then define the ambiguity aversion parameter as 1 less the matching probability. Similar to the non-parametric uncertainty and risk preference measures, a value of 1 corresponds to extreme ambiguity aversion while a number of 0 means extreme ambiguity seeking preferences. A parameter value of 0.5 implies ambiguity neutrality (see appendix D). In this two-dimensional state space, the ambiguity preference measure corresponds to the ambiguity preference parameter α of the α-MEU model by Ghiradato et al. (2004). As before, I compute a synthetic measure of ambiguity aversion defined as the average ambiguity aversion obtained from both tasks.

Panel A shows that subjects are on average significantly ambiguity averse (>0.5) in both tasks (t-test: p-value < 0.01). Combining the two tasks again reduces the variance of the ambiguity aversion measure significantly, which I interpret as evidence that combining the two measures allows for correcting for outliers. In the remainder of the analysis, the paper thus uses predominantly the combined measure of ambiguity aversion (baseline). However, since risk task 1 has fewer multiple switchers, I also use this measure of ambiguity aversion as robustness.

Similar to the risk preference measures, Panel C shows that the ambiguity preference measures obtained from the two tasks are not related to each other.

6 Explaining uncertainty aversion

This section explores the underlying reasons for the subjects' uncertainty aversion. The expected utility of Lotto lotteries can depend on both the utility function (risk preferences) and the attitude towards a range of probability distributions for each of the possible scenarios (ambiguity preferences). This section analyses whether the observed behaviour can be explained by risk preferences, ambiguity preferences, or both.

Section 6.1 uses a simple non-paramatric analysis of the experimental data, section 6.2 then goes on to estimate a parametric utility model that allows for both risk and ambiguity preferences. Section 6.3 examines the impact of replacing the two possible payoffs of the Lotto lotteries into a continuous range of payoffs.

6.1 Non-parametric analysis

In first step, I conduct a simple non-parametric analysis of the subjects' uncertainty preferences. I regress the subjects' uncertainty preference measures on the non-parametric measures of risk and ambiguity preferences. This analysis is carried out for two sets of measures. The baseline analysis uses the combined measures of uncertainty, risk, and ambiguity aversion. In addition, as robustness check, the analysis also uses the measures of uncertainty, risk and ambiguity aversion obtained for the tasks with the lower number of multiple switchers. The conjecture is that the lower the number of multiple switchers, the more reliable the experimental data (i.e., fewer measurement errors).

Table 7 shows that risk preferences can indeed explain the observed behaviour in the uncertainty tasks. In all specifications, the risk aversion coefficients are significantly different from zero, at high confidence levels. In addition, the explained variance of uncertainty aversion is substantial, reaching up to 39% in the robustness specification. Hence, this analysis shows strong support for the hypothesis that subjects behave according to subjective expected utility, i.e., the compound lottery model proposed in section 2.3.

However, the table shows that the ambiguity aversion coefficients are also highly significant, regardless of the specification. While in comparison to the risk-based explanation the association is slightly lower, this suggests that subjects are not fully confident about their subjective probabilities, and hence attribute some ambiguity to them. The pure risk model of decision making under uncertainty cannot however not capture such behaviour.

Finally, when using both risk and ambiguity preferences to predict the subjects' uncertainty aversion, the explained variance is highest, reaching 41% in the robustness specification. Both risk and ambiguity preferences are significantly different from 0, and are therefore important to explain the subject's uncertainty aversion.

6.2 Parametric analysis

This section uses a parametric utility model to predict the subjects' switching points in the uncertainty tasks, and then compares them to their actual, observed switching points. In light

Table 7: Explaining uncertainty aversion (non-parametric analysis)

Panel A: Uncertainty aversion measure – baseline specification

Risk aversion measure	0.464***		0.433***
	(0.000)		(0.000)
Ambiguity aversion measure		0.577***	0.511***
		(0.005)	(0.008)
Constant	0.252***	0.199*	-0.003
	(0.000)	(0.068)	(0.977)
R^2	0.14	0.08	0.20
Observations	93	93	93

Panel B: Uncertainty aversion measure – robustness specification

Risk aversion measure	0.624***		0.582***
	(0.000)		(0.000)
Ambiguity aversion measure		0.551***	0.293**
		(0.002)	(0.049)
Constant	0.167***	0.217**	0.035
	(0.001)	(0.024)	(0.667)
R^2	0.39	0.10	0.41
Observations	93	93	93

The table presents the non-parametric analysis of uncertainty aversion using OLS regressions. Panel A reports the results using the combined measures of uncertainty, risk, and ambiguity aversion (the baseline specification). Panel B reports the results using the uncertainty aversion measure obtained from task 2, the risk aversion measure obtained from task 2, and the ambiguity aversion measure obtained from task 1 (the robustness specification). *p*-values are given in parenthesis below the coefficient estimates. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

of the results of the previous non-parametric analysis, the utility model should allow for both risk and ambiguity preferences. The model compound lottery model (1) presented in section 2.3 has therefore to be modified to include ambiguity preferences. A straightforward extension is to allow for ambiguity in the second-stage horse lotteries. Using the α-MEU utility model (Ghiradato et al., 2004) to capture ambiguity preferences, the expected utility of a bet B is then given as

$$U(B) = \sum_{s \in \mathcal{S}} p_s \left(\alpha \min_{\Phi} \sum_{c \in \mathcal{C}} \mu_c(B) u(x_{c,s}) + (1-\alpha) \max_{\Phi} \sum_{c \in \mathcal{C}} \mu_c(B) u(x_{c,s}) \right) \tag{2}$$

where Φ denotes the set of subjective probability distributions for the scenarios (instead of a single measure), thereby allowing for ambiguity. The parameter α captures the decision maker's attitude towards ambiguity. If $\alpha = 1$, only the worst case is considered; if $\alpha = 0$, only the best possible case is considered. As utility function, I use the constant relative risk aversion (power) utility model.

Starting with uncertainty task 2, the utility of the safe option (the degenerate roulette lottery) with a payoff $x \in [0, 10]$ is given as[8]

$$u(x) = \frac{x^{(1-\gamma)}}{1-\gamma}.$$

In case of risk-neutrality ($\gamma = 0$), the utility function simplifies to $u(x) = x$. In turn, the expected utility of the uncertain payoff of 10 points (the degenerate Lotto lottery) is given by

$$\alpha - MEU(10) = \alpha\, u(0) + (1-\alpha) u(10) = (1-\alpha)\, \frac{10^{(1-\gamma)}}{1-\gamma}.$$

In this two-dimensional state space, $\alpha = 0.5$ corresponds to ambiguity neutrality. Put differently, ambiguity neutrality reflects the fact that the subjects have no prior information about the prize in the Lotto lottery and should therefore attribute a 50% probability of winning 10 points (especially since subjects had the possibility to choose the winning colour).[9]

The subjects' utility function parameters are estimated from the results from the risk and ambiguity aversion tasks. The subjects' coefficient of relative risk aversion γ is obtained from the risk tasks, and the ambiguity parameter α is obtained from the ambiguity tasks. In this case, the α is equal to the non-parametric ambiguity preference measure.

Since uncertainty task 1 is identical to uncertainty task 2 other than adding the possibility of winning no prize with a probability of 50%, the analysis is identical to the uncertainty measure 1, and therefore also for the combined uncertainty measure.

Following section 6.1, the analysis is carried out for two sets of measures. The baseline analysis uses the combined measures of uncertainty, risk, and ambiguity aversion, and the robustness analysis uses the measures of uncertainty, risk, and ambiguity aversion obtained from the tasks with the lower number multiple switchers. Table 8 reports the results when regressing the actual switching points in the uncertainty tasks on the predicted switching points implied by the model

[8] Since the highest value of γ in the sample is below 1, the utility of a payoff of 0 is well defined and given by $u(0) = 0$.

[9] In the risk-only case the expected utility of the Lotto lottery is $0.5\, u(10)$. In the ambiguity-only case the expected utility of the Lotto lottery is $(1-\alpha)\, 10$. In the risk and ambiguity case, the expected utility of the Lotto lottery is $(1-\alpha)\, u(10)$.

Table 8: Explaining uncertainty aversion (parametric analysis)

Panel A: Uncertainty aversion switching point – baseline specification

	Risk aversion	Ambiguity aversion	Risk and ambiguity aversion
Predicted switching point	0.330***	0.399**	0.352***
	(0.003)	(0.023)	(0.000)
Constant	4.071***	3.776***	4.109***
	(0.000)	(0.000)	(0.000)
R^2	0.09	0.06	0.14
Observations	93	93	93

Panel B: Uncertainty aversion switching point – robustness specification

	Risk aversion	Ambiguity aversion	Risk and ambiguity aversion
Predicted switching point	0.640***	0.551***	0.520***
	(0.000)	(0.002)	(0.000)
Constant	2.874***	3.091***	3.415***
	(0.000)	(0.000)	(0.000)
R^2	0.39	0.10	0.41
Observations	93	93	93

The table presents the parametric analysis of uncertainty aversion using both risk and ambiguity aversion. Based on the estimated risk (γ) and ambiguity (α) preference parameters, the analysis predicts the switching points in the uncertainty tasks and compares them to the actual switching points using OLS regressions. I use an α-MEU model (Ghiradato et al., 2004) with a power utility function. For more details, see section 6.2. Panel A reports the result using the combined measures of uncertainty, risk, and ambiguity aversion (the baseline specification). Panel B reports the result using the uncertainty aversion measure obtained from task 2, the risk aversion measure obtained from task 2, and the ambiguity aversion measure obtained from task 1 (the robustness specification). p-values are given in parenthesis below. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

using the parameters estimated from the risk and ambiguity tasks. Panel A reports the results for the baseline analysis; panel B reports the results for the robustness test.

The parametric analysis largely confirms the results of the non-parametric regression analysis. There is a strong association between actual and predicted switching points when explaining the switching points in the uncertainty preference tasks by risk preferences only. In the robustness analysis (panel B), the explained variance reaches up to 39%. As before, ambiguity aversion can also explain uncertainty aversion. In comparison to the risk-based explanation, however, the explained variance is slightly lower. Finally, when using both risk and ambiguity preferences to predict the subjects' switching points, the association between actual and predicted switching points are highest, regardless of the specification used. In the robustness specification, the explained variance reaches 41%.

Taken together, these results show that both risk and ambiguity preferences are important to explain the subjects' attitude towards uncertain payoffs. To some extent, the empirical results confirm that decision makers tend to behave as predicted by subjective expected utility theory, as conjectured by Camerer and Weber (1992). Uncertain payments of Lotto lotteries are attributed some subjective probability, and subjects then evaluate the reduced lottery using subjective expected utility. The more risk averse a decision maker, the less she likes the uncertainty of the payoff of Lotto lotteries, preferring the (relatively) safe payoff of roulette lotteries.

Yet, ambiguity preferences matter. When including ambiguity preferences, the predicted behaviour of subjects is closer to their actual behaviour. This seems intuitive, as decision makers have no information about the actual prize in the Lotto lotteries, such it is natural to conceive that they do not form precise subjective probabilities for each of the prizes, but rather consider a range of probabilities. If decision makers are ambiguity averse, this makes Lotto lotteries less attractive compared to roulette lotteries with complete information. Risk and ambiguity aversion thus work in the same direction.

The table also shows that the intercept of the regressions is always significantly positive. This means that the predicted switching points are consistently too low. Given the model and model parameters, subjects are expected to switch earlier than in the actual tasks. Put differently, they are less uncertainty averse than expected. This pattern is also visible form the descriptive statistics presented in section 5: while subjects are on average risk and ambiguity averse, they are not uncertainty averse – although risk and ambiguity aversion should explain uncertainty aversion.

6.3 Continuous uncertain payoffs

While the Lotto lotteries in the two uncertainty tasks have complete uncertainty about the payoff, these payoffs can take only two different values, one of which is positive. This implies that these Lotto lotteries are effectively very similar to the ambiguous option in the ambiguity preference task 2. More precisely, option B could be interpreted as a draw from an ambiguous box – a prize of 10 points with unknown probability.[10] Hence, by offering only two possible values for the uncertain payoff, subjects might be directly induced to think about the probabilities for each of the scenarios, and thus have uncertain probabilities in mind, rather than uncertain payoffs. This might explain the strong explanatory power of ambiguity aversion for uncertainty aversion documented before.

Offering only two possible payoffs is in fact a departure from the general concept of Lotto lotteries, in which subjects do not have any information about the payoff. The experimental literature in psychology for example does not restrict the payoffs to take on only a few possible values. Instead, these studies only indicate a possible range for the payoffs, allowing for all potential payoffs within that range. The advantage of leaving the set of payoffs (almost completely) unspecified is that subjects are less likely to jump into probability considerations for the unknown payoff.

Yet, decision tasks allowing for a continuous range of payoffs come with several drawbacks. First, receiving a payoff from a continuous range of payoffs cannot be easily transformed into draws of balls with different colours from a box, as used in the uncertainty choice tasks. As a consequence, it is much more difficult to implement a mechanism that avoids subjects to form non-symmetric subjective probability distributions over the range of the payoffs. Such a

[10]Different from standard tasks to measure ambiguity preferences, however, the alternative choice (option A) is a sure payment.

procedure would require subjects to decide the specific payoff for each of the different colours drawn from the box. This is not possible for a continuous payoff. Hence, without such a mechanism, decision makers might believe that the expected payoff is rather low, e.g., to save on the experimenter's budget.

Second, allowing for continuous ranges of payoffs might reduce size of the empirically observed magnitude of uncertainty preferences. To the extent the risk preferences can explain uncertainty preferences, a continuous payoff range setting attributes by definition a higher probability mass around the mid-point relative to a setting that allows only for the two endpoints of a range. The binary setting is more extreme, and uncertainty preferences are therefore likely to be more visible.

Finally, continuous payoffs do not allow for an unambiguous mapping between risk aversion and uncertainty aversion. With two payoffs, a 50% probability for obtaining a high payoff is the only possible symmetric probability distribution in the mind of subjects. If payoffs are continuous, there are many possible symmetric probability distributions, such as a truncated normal distribution or a uniform distribution. These (subjective) probability distributions are however unobservable.

Despite these challenges, I conducted another round of experimental sessions to examine the impact of changing the assumption of two possible payoffs into a continuous range of payoffs. In these session I use a new task to measure the subjects' uncertainty aversion (*uncertainty task 3*), which is a variant of uncertainty task 2. Instead of offering an uncertain payoff of either 0 or 10, subjects are offered an uncertain payoff in the range from 0 to 10 (see appendix C). The degenerate roulette lottery is identical to uncertainty task 2. Similar to uncertainty task 2, subjected are expected to first prefer the Lotto lottery over the safe payment. As the safe payment is increasing, subjects are expected to switch to the safe payment (i.e., the roulette lottery) at some point. The earlier they switch, the more they are uncertainty averse.

The second round of experiments also includes the tasks used in the robustness specification of the main analysis, i.e., uncertainty task 2, risk task 2, and ambiguity task 1. The experiments were conducted in December 2019, again at the ExpressLab of Royal Holloway (University of London). 100 students participated in the study, with an average age of about 20 years.

Table 9 shows that the replication of the three preference tasks used in the main analysis yields similar results in this second sample. As before, uncertainty task 2 shows that subjects are slightly uncertainty averse on average, but the value of 0.527 is not statistically different from 0.5 (see panel A). The risk and ambiguity aversion measures indicate, as before, that subjects are risk and ambiguity averse.

The uncertainty preference parameter obtained from the new uncertainty task 3 confirms that subjects are uncertainty averse. Different from uncertainty task 2, this average is significantly larger than 0.5 (although the point estimate is slightly lower than the average of task 2). Panel B shows that the two uncertainty preference parameters are highly correlated, reaching a linear correlation of 61%. A paired t-test confirms that both measures are not statistically different from each other. Taken together, these results show that subjects treat a range of payoffs from 0 to 10 very similar to the binary case with a payoff that can be either 0 or 10. The fact that subjects could not influence the distribution of the payoffs in this task did not lead to an increase in uncertainty aversion.

Panel C repeats the non-parametric analysis of uncertainty preferences when allowing the

Table 9: Continuous payoffs

Panel A: Descriptive statistics of non-parametric measures

	Observations	Mean	Standard deviation	Lowest	Highest
Uncertainty aversion 2	100	0.527	0.164	0.05	0.95
Uncertainty aversion 3	100	0.522*	0.130	0.25	0.95
Risk aversion 2	100	0.560***	0.151	0.25	0.95
Ambiguity aversion 1	100	0.541***	0.124	0.15	0.95

Panel B: Correlation statistics – non-parametric uncertainty aversion measures

	Uncertainty aversion 2	Uncertainty aversion 3
Uncertainty aversion 2		0.528***
Uncertainty aversion 3	0.608***	

Panel C: Explaining uncertainty aversion (non-parametric)

Risk aversion measure	0.500***		0.425***
	(0.000)		(0.000)
Ambiguity aversion measure		0.457***	0.313***
		(0.000)	(0.000)
Constant	0.244***	0.275***	0.115**
	(0.000)	(0.000)	(0.032)
R^2	0.33	0.19	0.41
Observations	100	100	100

Panel D: Explaining uncertainty aversion (parametric)

	Risk aversion	Ambiguity aversion	Risk and ambiguity aversion
Predicted switching point	1.099***	0.456***	0.383***
	(0.000)	(0.000)	(0.000)
Constant	0.500	3.413***	3.920***
	(0.634)	(0.000)	(0.000)
R^2	0.18	0.19	0.33
Observations	100	100	100

The table summarizes the results of the second round of experiments. Panel A reports the non-parametric uncertainty, risk, and ambiguity aversion measures derived from the switching points. Uncertainty aversion measure 2 is based on two possible payoffs; uncertainty aversion measure 3 is based on the full range of payoffs. Significance of the difference to 0.5 is estimated using a t-test. Panel B reports the correlation statistics between the two uncertainty aversion measures. The lower part of the panel presents the Pearson correlation, the upper part the Spearman correlation. Panel C reports the non-parametric analysis of the uncertainty aversion parameter obtained from uncertainty task 3 using OLS regressions. Panel D presents the parametric analysis of uncertainty aversion using both risk and ambiguity aversion using OLS regressions. Based on the estimated risk (γ) and ambiguity (α) preference parameters, the analysis predicts the switching points in the uncertainty tasks and compares them to the actual switching points. I use an α-MEU model (Ghiradato et al., 2004) with a power utility function. P-values are given in parenthesis below the coefficient estimates. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. For a detailed description of the various measures see appendices C and D.

uncertain payoff to lie in a range from 0 to 10. The results are very similar to those of the main analysis, see table 7. Both risk and ambiguity preferences are strongly related to uncertainty preferences, with both coefficients being highly significant.

Finally, panel D replicates the parametric analysis of uncertainty preferences. This requires an assumption about the subjective probability distribution of the risk-only case (as subjective probability distributions are not observable). In this analysis, I assume that subjects attribute a uniform distribution to the entire range of payoffs from 0 to 10. Since the uniform distribution over all possible payoffs reduces the variance of expected payoffs, the explained variance of predicted switching points for actual switching points is in the risk-only case lower compared to the binary case. Surprisingly, in the ambiguity-only specification, the R^2 between actual and predicted switching points increases slightly. Since the best and the worst cases are identical for a continuous range of payoffs and the two endpoints only, the α-MEU expected value of the Lotto lottery remains unchanged. Finally, when considering both risk and ambiguity preferences to explain uncertainty preferences, the association between actual and predicted switching points is most pronounced, albeit slightly lower than in the main analysis.

Overall, the results of this section show that replacing the binary payoff space in the Lotto lottery with a continuous payoff range does not change the subjects' uncertainty aversion. By and large, subjects seem to treat both types of uncertain payoffs identical, regardless of the information about the uncertain payoff given. From a more general point of view, this means that the results of this study can be easily compared to the findings in the psychology and management science literature which usually assumes a range of uncertain payoffs in their experiments.

7 Related literature

The two-stage compound lottery model outlined in this paper – both the risk-only version as well as the extension that allows for ambiguity preferences – offers a framework to better understand decision making under the uncertainty of a Lotto lottery. Most of all, it provides a convenient set-up to empirically disentangle risk, ambiguity, and uncertainty preferences.

The compound lottery model is however not the only possibility to formalize Lotto lotteries. In fact, the theoretical literature has proposed a variety of models to analyze decision making under uncertainty when there is not enough information to work within the expected utility framework. While these models provide valuable insights, it is not straightforward to directly take them to the experimental data.

Preferences over Lotto lotteries can also be modelled using belief and plausibility functions following Dempster (1967) and Shafer (1976).[11] Instead of assigning a probability to each of the possible outcomes (as in expected utility theory), belief functions give the lower bound on the probability for any given outcome, while plausibility functions give their upper bound. Belief and plausibility functions are thus non-additive probabilities (or capacities). In the introductory example, the belief (Bel) and plausibility (Pl) functions for a payoff of 0 (white ball) are $Bel(0) = Pl(0) = 0.5$; they coincide since its probability is objectively given. For a payoff of 1 (red ball) or 2 (yellow ball), however, they differ: Their lower bound is given by a 0% probability, $Bel(1) = Bel(2) = 0$, while their upper bound is given by a 50% probability, $Pl(1) = Pl(2) = 0.5$.

[11] For an excellent recent literature review of decision-theoretic models using belief functions, see Denoeux (2019).

Preferences over Lotto lotteries can hence be conceived as preferences over belief or plausibility functions. Lotto lotteries can therefore evaluated using the Choquet expected utility criterion, where the capacity is structured as a belief function. Thus, the uncertain outcomes of Lotto lotteries directly translate into probabilistic ambiguity about the set of possible outcomes.

These ideas have been formalised, among others, by Jaffray (1989), Mukerji (1997) and Ghiradato (2001). In Ghiradato (2001), for example, the decision maker only sees choices as maps from states into consequences. That is, each choice that a decision maker considers for a given state, may lead to a set of consequences, or outcomes. In this setting, decision makers have subjective probability distribution over states of the world, but the distribution over the final outcomes is no longer additive (i.e., they are belief functions), thus allowing for ambiguity. The works of this literature also propose applying the Hurwicz (1951) criterion to the belief (and plausibility) functions. That is, similar to the empirical α-model estimated in this paper, some weight is attributed to the worst case for the decision maker, while some weight is attributed to the best case.

Viero (2009) takes a different approach. She proposes an extension of the Anscombe and Aumann (1963) framework by replacing the second-stage roulette lottery of Anscombe-Aumann by a set of roulette lotteries. In her representations, the decision maker first evaluates acts by computing, for each state, the expected utility of the best and the worst second-stage lotteries, and then weighs them according to her optimism/pessimism. Finally, she computes her overall expected utility using these weighted utilities together with unique subjective probabilities over the states. Different from the model proposed in this paper, first and second stage lotteries are reversed: the probabilities for states are subjective, but the second-stage probabilities for roulette lotteries are objective.

8 Concluding remarks

Analysing decision making under uncertainty when payoffs are inherently uncertain, like the Lotto lotteries studied in this paper, has not been at the centre of research in economics or psychology. Yet, Lotto lotteries arise in many real-life situations. This paper contributes to a better understanding of Lotto lotteries from both a theoretical and empirical perspective.

The key result is to show that both risk and ambiguity preferences are important to explain subjects' aversion to uncertain payoffs. While the importance of risk preferences for uncertainty aversion has been highlighted early on (Camerer and Weber, 1992), the role of ambiguity preferences has been largely overlooked so far. Rather, aversion to "ambiguous outcomes" has been considered as a different trait, sometimes even independent of ambiguity preferences. For example, Camerer and Weber (1992) write that

> "If people are averse to ambiguity about which *outcome* will occur [...], then they are risk averse and consistent with expected utility. But if people are averse to ambiguity about the *probability* of an outcome, they are ambiguity averse and inconsistent with subjective expected utility. The two kinds of ambiguity are fundamentally different."

Different from this conjecture, this paper suggests thinking about uncertain outcomes not as a black box, but rather as a set of possible outcomes with (subjective) probabilities attached to each of them. If these subjective probabilities are unique, risk aversion can perfectly explain uncertainty aversion. However, if these subjective probabilities are not singleton (but rather consist of a set of probabilities), ambiguity aversion has also a role to explain uncertainty aversion. The empirical finding that both risk ambiguity preferences matter provides evidence for the latter. This means that ambiguity about outcomes is ultimately closely linked to ambiguity about probabilities.

These findings have some important implications. Given that many decisions in our daily lives involve uncertain outcomes, this paper highlights the importance of taking into account individual ambiguity preferences when making such decisions. While risk preferences are increasingly being measured in everyday business applications (e.g., in private banking), a systematic measurement of ambiguity preferences is missing so far.

The insight that both ambiguity and risk preferences matter when payoffs are uncertain is also reassuring from a theoretical perspective. Most decision-theoretic models that capture features similar to the Lotto lotteries analysed in this paper build on the concept of belief functions introduced by Dempster (1967) and Shafer (1976). Given the non-additive nature of belief functions, these models directly imply a close relation between uncertain outcomes and ambiguity about probabilities. The results of this paper thus confirm these models empirically.

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Appendix A: Transforming the compound lottery model into Anscombe-Aumann

The compound Lotto lottery model is very close to the Anscombe-Aumann model, as both consist of a combination of a roulette and a horse lottery. While the Ascombe-Aumann model combines a horse lottery over states with a roulette lottery over payoffs, the Lotto lottery model combines a roulette lottery over states with a horse lottery over scenarios. This appendix shows that the compound Lotto lottery model is a special case of the the Anscombe-Aumann model.
The model introduced in section 2.3 suggests the following representation of preferences over Lotteries:

$$B \succ B' \Leftrightarrow U(B) > U(B') \Leftrightarrow \sum_{s\in\mathcal{S}} p_s \left(\sum_{c\in\mathcal{C}} \mu_c(B)u(x_{c,s})\right) > \sum_{s\in\mathcal{S}} p_s \left(\sum_{c\in\mathcal{C}} \mu_c(B)u(x_{c,s})\right)$$

for some $\mu_c(B)$ and $\mu_c(B')$. Note that $x_{c,s}$ denotes the payoff of the bets in state s under scenario c.
First, we formally introduce the global scenarios $\mathcal{G}$. A global scenario g is a combination of possible scenarios for each of the bets. The set of all possible combinations of local scenarios $\mathcal{C}$ forms the set of global scenarios $\mathcal{G}$. For example, if there are two bets, then $\mathcal{G} = \mathcal{C} \times \mathcal{C}$. The subjective probability for each of the global scenarios μ_g can be inferred from the subjective probabilities for the scenarios μ_c. Hence, we can replace the local scenarios c with the global scenarios g. More precisely, if state s occurs, the subjective expected utility of bet B is

$$\sum_{c\in\mathcal{C}} \mu_c(B)u(x_{c,s}) = \sum_{g\in\mathcal{G}} \mu_g u(x_{g,s}(B))$$

Therefore:

$$\sum_{s\in\mathcal{S}} p_s \left(\sum_{c\in\mathcal{C}} \mu_c(B)u(x_{c,s})\right) = \sum_{s\in\mathcal{S}} p_s \left(\sum_{g\in\mathcal{G}} \mu_g u(x_{g,s}(B))\right)$$

Next we switch the summation terms:

$$\sum_{s\in\mathcal{S}} p_s \left(\sum_{g\in\mathcal{G}} \mu_g u(x_{g,s}(B))\right) = \sum_{g\in\mathcal{G}} \mu_g \left(\sum_{s\in\mathcal{S}} p_s u(x_{g,s}(B))\right)$$

Note that $\sum_{s\in\mathcal{S}} p_s u(x_{g,s}(B))$ gives the expected utility of the roulette lottery B. Instead of summing over the observable states $s \in \mathcal{S}$, we can sum over the set of the possible payoffs $x \in \mathcal{X}$. The expected utility of the roulette lottery B is:

$$\sum_{s\in\mathcal{S}} p_s u(x_s(B)) = \sum_{x\in\mathcal{X}} p_x(B)u(x)$$

Hence:

$$\sum_{g\in\mathcal{G}} \mu_g \left(\sum_{s\in\mathcal{S}} p_s u(x_{g,s}(B))\right) = \sum_{g\in\mathcal{G}} \mu_g \left(\sum_{x\in\mathcal{X}} p_{g,x}(B)u(x)\right)$$

where $p_{g,x}(B)$ denotes for bet B the probability of payoff x to occur, given the global scenario g. Since we are operating on roulett lotteries, these probability are objectively given.
The last step is to replace the global scenarios G with the states S of the Ascombe-Aumann model. This is merely a re-labeling. The only difference is that the Ascombe-Aumann states are observable ex-post, but the global scenarios are not. Note that the states in the Ascombe-Aumann model as well as the global states have subjective probabilities μ attached to each of the state/global scenario. Hence:

$$\sum_{g\in\mathcal{G}} \mu_g \left(\sum_{x\in\mathcal{X}} p_{g,x}(B)u(x)\right) = \sum_{s\in\mathcal{S}} \mu_s \left(\sum_{x\in\mathcal{X}} p_{s,x}(B)u(x)\right)$$

This gives us the Anscombe-Aumann model:

$$B \succ B' \Leftrightarrow U(B) > U(B') \Leftrightarrow \sum_{s\in\mathcal{S}} \mu_s \left(\sum_{x\in\mathcal{X}} p_{s,x}(B)u(x) \right) > \sum_{s\in\mathcal{S}} \mu_s \left(\sum_{x\in\mathcal{X}} p_{s,x}(B')u(x) \right)$$

where $p_{s,x}(B)$ denotes the objective probability of outcome x to occur in state s for bet B. That is, $\sum_{x\in\mathcal{X}} p_{s,x}(B)u(x)$ gives the expected utility of bet B for state s. Furthermore, μ_s denote the subjective probabilities for each of the states $s \in \mathcal{S}$.

Example revisited

The decision maker has the choice between drawing a ball from two different urns (F and G), each of which can have two possible compositions (white and red) or (white and yellow), and therefore also different payoffs. Hence, there are four possible *global* scenarios $\mathcal{G}$.

$$\begin{aligned} g_1 &= (yellow, yellow) \text{ with probability } \mu_1 \\ g_2 &= (yellow, red) \text{ with probability } \mu_2 \\ g_3 &= (red, yellow) \text{ with probability } \mu_3 \\ g_4 &= (red, red) \text{ with probability } \mu_4 \end{aligned}$$

where each pair denotes the colour of the coloured ball in the first urn (F) and the colour of the coloured ball in the second urn (G). The decision maker does not know which global scenario corresponds to the true scenario. Since there are no objective probabilities for each of the scenarios, the decision maker attributes subjective probability distributions μ_g to each of them, such that $\sum_g \mu_g = 1$. In this context, a bet on one urn is hence a list of payoffs for all possible global scenarios and all possible states of the world (whose probabilities are objectively given).
Hence, bet F is given as:

	Scenario 1 μ_1	Scenario 2 μ_2	Scenario 3 μ_3	Scenario 4 μ_4
coloured (p=0.5)	2	2	1	1
white (p=0.5)	0	0	0	0

And bet G given as:

	Scenario 1 μ_1	Scenario 2 μ_2	Scenario 3 μ_3	Scenario 4 μ_4
coloured (p=0.5)	2	1	2	1
white (p=0.5)	0	0	0	0

It is natural to assume that the decision maker weighs all payoffs with their subjective probability. Hence, bet F is preferred over G if:

$$\begin{aligned} F &\succ G \\ U(F) &> U(G) \\ 0.5u(0) + 0.5(u(2)\mu_1 + u(2)\mu_2 + u(1)\mu_3 + u(1)\mu_4) &> 0.5u(0) + 0.5(u(2)\mu_1 + u(1)\mu_2 + u(2)\mu_3 + u(1)\mu_4) \\ \mu_2 &> \mu_3 \end{aligned}$$

Note that this is equivalent to the previous model, if we set $\mu_2 = \mu_F(1-\mu_G)$ and $\mu_3 = (1-\mu_F)\mu_G$. Then we have again $\mu_F > \mu_G$. A different way of describing the two bets is by attributing (subjective) probabilities for each of the outcomes (the reduced lottery):

$$F = \begin{cases} \text{white ball } (x^F = 0) & \text{with probability } 0.5(\mu_1 + \mu_2 + \mu_3 + \mu_4) \\ \text{red ball } (x^F = 1) & \text{with probability } 0.5(\mu_3 + \mu_4) \\ \text{yellow ball } (x^F = 2) & \text{with probability } 0.5(\mu_1 + \mu_2) \end{cases}$$

and

$$G = \begin{cases} \text{white ball } (x^G = 0) & \text{with probability } 0.5(\mu_1 + \mu_2 + \mu_3 + \mu_4) \\ \text{red ball } (x^G = 1) & \text{with probability } 0.5(\mu_2 + \mu_4) \\ \text{yellow ball } (x^G = 2) & \text{with probability } 0.5(\mu_1 + \mu_3) \end{cases}$$

Appendix B: Numerical example for preference of roulette lotteries over Lotto lotteries

This appendix gives some numerical illustration for the four reasons why decision makers might prefer roulette lotteries (urn F in the example) over Lotto lotteries (urn G in the example), as discussed in section 3.2: (1) risk aversion, (2) non-symmetric subjective probabilities, (3) ambiguity aversion, and (4) non-symmetric ambiguity.

1. Risk aversion: Suppose the decision maker has a log utility function $u(x) = \ln(x)$, and symmetric subjective probabilities for the coloured ball in urn G to be either yellow or red ($\mu(red) = \mu(yellow) = 0.5$) (no ambiguity):

$$\begin{aligned} EU(F) &> SEU(G) \\ 0.5\ln(2) &> 0.5\,(0.5\ln(1) + 0.5\ln(3)) \\ 0.347 &> 0.275 \\ F &\succ G \end{aligned}$$

2. Non-symmetric subjective probabilities: Suppose the decision maker has a linear utility function $u(x) = x$, but non-symmetric subjective probabilities for the coloured ball in urn G to be either yellow or red, $\mu(red) = 0.6$ and $\mu(yellow) = 0.4$ (no ambiguity):

$$\begin{aligned} EU(F) &> SEU(G) \\ 0.5 \cdot 2 &> 0.5\,(0.6 \cdot 1 + 0.4 \cdot 3) \\ 1 &> 0.9 \\ F &\succ G \end{aligned}$$

3. Ambiguity aversion: Suppose the decision maker has a linear utility function $u(x) = x$, but a set $\mathcal{P}$ of probabilities for the coloured ball in urn G to be either yellow or red, such that $\mathcal{P}(red) = [0, 1]$, i.e., there is ambiguity. By additivity, we have $\mathcal{P}(yellow) = [0, 1]$. The decision maker is ambiguity averse ($\alpha = 0.6$), using the α-MEU model by Ghiradato et al. (2004):

$$\begin{aligned} EU(F) &> \alpha - MEU(G) \\ 0.5 &> 0.5\left(0.6\inf_{p\in\mathcal{P}}(red)EU[G] + 0.4\sup_{p\in\mathcal{P}}(red)EU[G]\right) \\ 0.5 \cdot 2 &> 0.5\,(0.6 \cdot 1 + 0.4 \cdot 3) \\ 1 &> 0.9 \\ F &\succ G \end{aligned}$$

4. Non-symmetric ambiguity: The decision maker has a linear utility function $u(x) = x$, but a non-symmetric set $\mathcal{P}$ of probabilities for the coloured ball in urn G to be either yellow or red, such that such that $\mathcal{P}(red) = [0.5, 1]$, i.e., there is ambiguity. By additivity, we have $\mathcal{P}(yellow) = [0, 0.5]$. The decision maker is ambiguity neutral ($\alpha = 0.5$), using the α-MEU model by Ghiradato et al. (2004):

$$\begin{aligned} EU(F) &> \alpha - MEU(G) \\ 0.5 &> 0.5\left(0.5\inf_{p\in\mathcal{P}}(red)EU[G] + 0.5\sup_{p\in\mathcal{P}}(red)EU[G]\right) \\ 0.5 \cdot 2 &> 0.5\,(0.5 \cdot 1 + 0.5 \cdot 2) \\ 1 &> 0.75 \\ F &\succ G \end{aligned}$$

Appendix C: Incentivized decision tasks

This appendix presents the incentivized decision tasks to measure risk, ambiguity, and uncertainty preferences. Before each task, subjects were presented examples of the choice tasks to familiarize themselves with the design. In addition, subjects were asked several control questions to ensure that they understood the tasks. Note that the actual wording of the tasks is slightly different from the appendix since each task was presented on a sequence of computer screens.

General instructions:

This part consists of 6 tasks. In completing these tasks you can earn points; points will be converted into GBP at a rate of 1 to 5. This means that you receive GBP 1 for every 5 points you earn. Your earnings from the 6 tasks will be paid out to you at the end of the session together with your show-up reward of GBP 2. Please read carefully the instructions before each task since the points you can earn depend on your answers. Although some of the tasks might appear similar, they are all different. The points from each task will be determined at the end of the session. Each task is independent from choices you made in previous tasks.

In each of the 6 tasks you need to fill in a decision table. Each decision table consists of various situations. Each situation offers you a choice between two options. At the end of the session, the computer will – for each task – randomly select one out of the situations. Then, depending on your choice, you can earn some money. Note that even though you will make many decisions when filling out a decision table, only one of these will determine the points you earn. However, you don't know in advance which situation will be selected (they are equally likely to be selected).

Risk task 1: This tasks determines risk preferences by eliciting an uncertainty equivalent for a sequence of lotteries. The task is taken from decision sheet B of Chakravarty and Roy (2009). It is a simplified version of the Holt and Laury (2002) design.

The decision table of task 1 consists of 10 situations. Each situation offers you a choice between drawing a ball from two different boxes, box A or box B. Both boxes contain 10 balls, either white or black.

- *The composition of box A is identical in all 10 situations. There are 5 white balls and 5 black balls.*
- *The composition of box B changes from one situation to the next. The number of white balls increases incrementally from 0 white balls in situation 1 to 9 white balls in situation 10, while the number of black balls decreases accordingly.*

At the end of the session, the computer will randomly select one out of the 10 situations. Then, depending on whether you have chosen box A or box B in that situation, the computer will randomly draw one ball from that box. Depending on the colour of the ball, you earn the points indicated in the table.

In each situation, from which box do you prefer to draw a ball, box A or box B?

Situation	Box A: If a white ball is drawn you earn 6 points If a black ball is drawn you earn 4 points	Box B: If a white ball is drawn you earn 10 points If a black ball is drawn you earn 0 points	Your choices
1	5 white balls, 5 black balls	0 white balls, 10 black balls	Box A ◯ ◯ Box B
2	5 white balls, 5 black balls	1 white ball, 9 black balls	Box A ◯ ◯ Box B
3	5 white balls, 5 black balls	2 white balls, 8 black balls	Box A ◯ ◯ Box B
4	5 white balls, 5 black balls	3 white balls, 7 black balls	Box A ◯ ◯ Box B
5	5 white balls, 5 black balls	4 white balls, 6 black balls	Box A ◯ ◯ Box B
6	5 white balls, 5 black balls	5 white balls, 5 black balls	Box A ◯ ◯ Box B
7	5 white balls, 5 black balls	6 white balls, 4 black balls	Box A ◯ ◯ Box B
8	5 white balls, 5 black balls	7 white balls, 3 black balls	Box A ◯ ◯ Box B
9	5 white balls, 5 black balls	8 white balls, 2 black balls	Box A ◯ ◯ Box B
10	5 white balls, 5 black balls	9 white balls, 1 black ball	Box A ◯ ◯ Box B

Risk task 2: This task determines risk preferences by eliciting a certainty equivalent for a lottery. The task is adapted from task 5 of Vieider (2018).

The decision table of task 2 consists of 14 situations. Each situation offers you a choice between two options:

- *Option 1 offers you to draw a ball from a box which contains 5 green balls and 5 red balls. If a green ball is drawn, you earn 20 points. Option 1 is identical in each situation.*
- *Option 2 offers you a sure number of points. The number of points increases from one situation to the next.*

At the end of the session, the computer will randomly select one out of the 14 situations. If you have chosen option 1, the computer the computer will randomly draw one ball from a box that contains 5 green balls and 5 red balls. If the colour of the ball drawn is green you earn 20 points, and nothing otherwise. If you have chosen option 2, you receive the number of points as indicated.

Which option do you prefer each situation? Drawing a ball from a box with a 50% probability to earn 20 points (option 1) or a sure number of points (option 2)?

Situation	Option 1: If a green ball is drawn you earn 20 points If a red ball is drawn you earn 0 points	Option 2: Sure number of points	Your choices
1	Draw from a box with 5 green & 5 red balls	2 points for sure	Option 1 ◯ ◯ Option 2
2	Draw from a box with 5 green & 5 red balls	4 points for sure	Option 1 ◯ ◯ Option 2
3	Draw from a box with 5 green & 5 red balls	5 points for sure	Option 1 ◯ ◯ Option 2
4	Draw from a box with 5 green & 5 red balls	6 points for sure	Option 1 ◯ ◯ Option 2
5	Draw from a box with 5 green & 5 red balls	7 points for sure	Option 1 ◯ ◯ Option 2
6	Draw from a box with 5 green & 5 red balls	8 points for sure	Option 1 ◯ ◯ Option 2
7	Draw from a box with 5 green & 5 red balls	9 points for sure	Option 1 ◯ ◯ Option 2
8	Draw from a box with 5 green & 5 red balls	10 points for sure	Option 1 ◯ ◯ Option 2
9	Draw from a box with 5 green & 5 red balls	11 points for sure	Option 1 ◯ ◯ Option 2
10	Draw from a box with 5 green & 5 red balls	12 points for sure	Option 1 ◯ ◯ Option 2
11	Draw from a box with 5 green & 5 red balls	13 points for sure	Option 1 ◯ ◯ Option 2
12	Draw from a box with 5 green & 5 red balls	14 points for sure	Option 1 ◯ ◯ Option 2
13	Draw from a box with 5 green & 5 red balls	16 points for sure	Option 1 ◯ ◯ Option 2
14	Draw from a box with 5 green & 5 red balls	18 points for sure	Option 1 ◯ ◯ Option 2

Ambiguity task 1: This task determines ambiguity preferences by eliciting a matching probability for an ambiguous lottery. The task extents the Ellsberg (1961) thought experiment to different situations, similar to Lauriola and Levin (2001) and Butler et al. (2014).

The decision table of task 3 has 11 situations. Similar to task 1, each situation offers you a choice between drawing a ball from two different boxes, box 1 or box 2. Both boxes contain 10 balls, either white or black.

- *The composition of box 1 changes from one situation to the next. While the number of balls in one colour (e.g., white) increases incrementally from 0 to 10, the number of balls of the other colour (e.g., black) decreases accordingly.*
- *The composition of box 2 is identical in each situation. However, you don't know how many balls are white and how many balls are black. Any combination is possible. There might be from 0 to 10 white balls, with the remaining balls being black.*

One ball will be drawn from the box you choose. The points you can earn depend on the colour of the ball drawn. Only one colour yields some points. You can choose whether the colour that yields points is white or black. Please choose the colour of the ball that provides you points:

- *white*
- *black*

In each of the 11 situations, we would like you to indicate from which box (box 1 or box 2) you prefer drawing a ball. As explained before, both boxes contain 10 balls, either white or black.[12]

- *The composition of box 1 changes from one situation to the next. The number of white balls increases incrementally from 0 white balls in situation 0 to 10 white balls in situation 10, while the number of black balls decreases accordingly.*
- *The composition of box 2 is identical in all situations. However, the exact composition of box 2 is unknown. Any combination of white and black balls is possible: there might be 10 white balls, or 10 black balls, or any other possible combination of white and black balls.*

At the end of the session, the computer will randomly select one out of the 11 situations. Then, depending on whether you have chosen box 1 or box 2 in that situation, the computer will randomly draw one ball from that box. If the colour of the ball is white you earn 10 points.[13]

In each situation, from which box do you prefer to draw a ball, box 1 or box 2?

[12] From this point onward, the actual text and decision table depend on the colour chosen. In this example, it is assumed that the selected colour is white. If the selected colour is black, the word "white" has to be replaced by "black", and vice versa.

[13] In practice, the ambiguous box (box 2) contained 7 balls of the winning colour. This was unknown to participants.

Situation	Box 1: If a white ball is drawn you earn 10 points If a black ball is drawn you earn 0 points	Box 2: If a white ball is drawn you earn 10 points If a black ball is drawn you earn 0 points	Your choices
0	0 white balls, 10 black balls	unknown composition	Box 1 ◯ ◯ Box 2
1	1 white ball, 9 black balls	unknown composition	Box 1 ◯ ◯ Box 2
2	2 white balls, 8 black balls	unknown composition	Box 1 ◯ ◯ Box 2
3	3 white balls, 7 black balls	unknown composition	Box 1 ◯ ◯ Box 2
4	4 white balls, 6 black balls	unknown composition	Box 1 ◯ ◯ Box 2
5	5 white balls, 5 black balls	unknown composition	Box 1 ◯ ◯ Box 2
6	6 white balls, 4 black balls	unknown composition	Box 1 ◯ ◯ Box 2
7	7 white balls, 3 black balls	unknown composition	Box 1 ◯ ◯ Box 2
8	8 white balls, 2 black balls	unknown composition	Box 1 ◯ ◯ Box 2
9	9 white balls, 1 black ball	unknown composition	Box 1 ◯ ◯ Box 2
10	10 white balls, 0 black balls	unknown composition	Box 1 ◯ ◯ Box 2

Ambiguity task 2: This task determines ambiguity preferences by eliciting a matching probability for an ambiguous lottery, similar to ambiguity task 1.

In task number 4, we present you another decision table with 14 situations. Similar to the previous task, each situation offers you a choice between drawing a ball from two different boxes, box X or box Y. Both boxes contain 20 balls, either white or black.

- *The composition of box X changes from one situation to the next. While the number of balls in one colour (e.g., white) increases from one situation to the next, the number of balls of the other colour (e.g., black) decreases accordingly.*
- *The composition of box Y is identical in each situation. However, you don't know the colour of the balls in box Y: They can be all white OR all black.*

One ball will be drawn from the box you choose. The points you can earn depend on the colour of the ball drawn. Similar to task 3, only one colour yields some points. You can choose whether the colour that yields points is white or black.

- *white*
- *black*

In each of the 14 situations of the decision table, we would like you to indicate from which box (box X or box Y) you prefer drawing a ball. As explained before, both boxes contain 20 balls, either white or black.[14]

- *The composition of box X changes from one situation to the next. While the number of black balls increases, the number of white balls decreases accordingly.*
- *The composition of box Y is identical in each situation. However, you don't know the colour of the balls in box Y: They can be all white OR all black.*

At the end of the session, the computer will randomly select one out of the 14 situations. Then, depending on whether you have chosen box X or box Y in that situation, the computer will randomly draw one ball from that box. If the colour of the ball is white you earn 10 points.[15]

In each situation, from which box do you prefer to draw a ball, box X or box Y?

Situation	Box X: If a white ball is drawn you earn 10 points If a black ball is drawn you earn 0 points	Box Y: If a white ball is drawn you earn 10 points If a black ball is drawn you earn 0 points	Your choices
1	18 white balls and 2 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
2	16 white balls and 4 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
3	14 white balls and 6 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
4	13 white balls and 7 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
5	12 white balls and 8 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
6	11 white balls and 9 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
7	10 white balls and 10 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
8	9 white balls and 12 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
9	8 white balls and 12 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
10	7 white balls and 13 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
11	6 white balls and 14 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
12	5 white balls and 15 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
13	4 white balls and 14 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y
14	2 white balls and 10 black balls	20 white balls OR 20 black balls	Box X ◯ ◯ Box Y

[14] From this point onward, the actual text and decision table depend on the colour chosen. In this example, it is assumed that the selected colour is white. If the selected colour is black, the word "white" has to be replaced by "black", and vice versa.

[15] In practice, the ambiguous box (box Y) contained 20 balls of the winning colour. This was unknown to participants.

Uncertainty task 1: This task determines uncertainty preferences by eliciting an uncertainty equivalent of a Lotto lottery.

In task number 5, we present you another decision table with 11 situations. Similar to the previous tasks, each situation offers you a choice between drawing a ball from two different boxes, box I or box J.

- *Box I contains 10 white balls and 10 black balls. If a black ball is drawn, you earn some points. The points you can earn increases from one situation to the next.*
- *Box J contains 10 white balls and 10 coloured balls, which can either be all yellow OR all blue. Box J is identical in each situation. Depending on the colour of the ball drawn, you can earn 10 points. Similar to previous tasks, you can choose whether the colour that yields points is yellow or blue. If a white ball is drawn, you don't earn any points.*

Please choose the colour of the ball that provides you points.

- *yellow*
- *blue*

In each of the 11 situations of the decision table, we would like you to indicate from which box you prefer drawing a ball. As explained before:[16]

- *Box I contains 10 white balls and 10 black balls. If a black ball is drawn, you earn some points. The points you can earn increases from 0 points to 10 points.*
- *Box J contains 10 white balls and 10 coloured balls, which can either be all yellow OR all blue. If a yellow ball is drawn, you earn 10 points. If a blue or a white ball is drawn, you earn no points. Box J is identical in each situation.*

At the end of the session, the computer will randomly select one out of the 11 situations. If you have chosen box I the computer the computer will randomly draw one ball from the box. If the colour of that ball is black, you receive the number of points as indicated. If you have chosen box J, the computer the computer will randomly draw one ball from the box. If the colour of that ball is yellow you earn 10 points, and nothing otherwise.[17]

In each situation, from which box do you prefer to draw a ball, box I or box J?

Situation	Box I: Composition: 10 white balls, 10 black balls If a white ball is drawn you earn 0 points	Box J: Composition: 10 white balls, 10 coloured balls (10 yellow OR 10 blue balls) If a white ball is drawn you earn 0 points	Your choices
0	If a black ball is drawn you earn 0 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
1	If a black ball is drawn you earn 1 point	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
2	If a black ball is drawn you earn 2 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
3	If a black ball is drawn you earn 3 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
4	If a black ball is drawn you earn 4 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
5	If a black ball is drawn you earn 5 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
6	If a black ball is drawn you earn 6 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
7	If a black ball is drawn you earn 7 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
8	If a black ball is drawn you earn 8 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
9	If a black ball is drawn you earn 9 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J
10	If a black ball is drawn you earn 10 points	If a yellow ball is drawn you earn 10 points	Box I ◯ ◯ Box J

[16] From this point onward, the actual text and decision table depend on the colour chosen. In this example, it is assumed that the selected colour is yellow. If the selected colour is blue, the word "yellow" has to be replaced by "blue", and vice versa.

[17] In practice, the uncertain box (box J) contained 10 balls of the winning colour. This was unknown to participants.

Uncertainty task 2: This task determines uncertainty preferences by eliciting a certainty equivalent of an ambiguous lottery.

In task number 6, we present you a final decision table with 11 situations. Each situation offers you a choice between two options:

- *Option A offers you a sure number of points. The number of points increases from one situation to the next.*
- *Option B offers you to draw a ball from a box which contains 10 balls, which can either be all yellow OR all blue. Option B is identical in each situation. Depending on the colour of the ball drawn, you can earn 10 points. Similar to the previous task, you can choose whether the colour that yields points is yellow or blue.*

Please choose the colour of the ball that provides you points.

- *yellow*
- *blue*

In each of the 11 situations of the decision table below, we would like you to indicate which option you prefer. As explained before:[18]

- *Option A offers you a sure number of points. The number of points increases from one situation to the next.*
- *Option B offers you to draw a ball from a box which contains 10 balls, which can either be all yellow OR all blue. If a yellow ball is drawn, you earn 10 points. If a blue ball is drawn, you earn no points. Option B is identical in each situation.*

At the end of the session, the computer will randomly select one out of the 11 situations. If you have chosen option A, you receive the number of points as indicated. If you have chosen option B, the computer the computer will randomly draw one ball from the box. If the colour of that ball is yellow you earn 10 points, and nothing otherwise.[19]
In each situation, which option do you prefer? A sure number of points (option A) or drawing a ball from a box with an unknown number of points (option B)?

Situation	Option A: Sure number of points	Option B: If a yellow ball is drawn you earn 10 points If a blue ball is drawn you earn 0 points	Your choices
0	0 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
1	1 point for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
2	2 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
3	3 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
4	4 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
5	5 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
6	6 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
7	7 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
8	8 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
9	9 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B
10	10 points for sure	10 yellow balls OR 10 blue balls	Option A ◯ ◯ Option B

[18] From this point onward, the actual text and decision table depend on the colour chosen. In this example, it is assumed that the selected colour is yellow. If the selected colour is blue, the word "yellow" has to be replaced by "blue", and vice versa.

[19] In practice, the uncertain option (option B) contained 10 balls of the losing colour. This was unknown to participants.

Uncertainty task 3: This task determines uncertainty preferences by eliciting a certainty equivalent of a continuous ambiguous lottery.[20]

In task number 7, we present you a final decision table with 11 situations. Each situation offers you a choice between two options:

- *Option X offers you an unknown prize between 0 and 10 points. Option X is identical in each situation.*
- *Option Y offers you a sure number of points. The number of points increases from one situation to the next.*

At the end of the session, the computer will randomly select one out of the 11 situations. If you have selected Option X, you earn an unknown prize between 0 and 10 points. If you have selected Option Y, you earn the number of points as indicated.

In each situation, which option do you prefer? Drawing a ball from a box with an unknown number of points (option X) or a sure number of points (option Y)?

Situation	Option X: Unknown prize between 0 and 10 points	Option Y: Sure number of points	Your choices
0	unknown prize	0 points for sure	Option X ◯ ◯ Option Y
1	unknown prize	1 point for sure	Option X ◯ ◯ Option Y
2	unknown prize	2 points for sure	Option X ◯ ◯ Option Y
3	unknown prize	3 points for sure	Option X ◯ ◯ Option Y
4	unknown prize	4 points for sure	Option X ◯ ◯ Option Y
5	unknown prize	5 points for sure	Option X ◯ ◯ Option Y
6	unknown prize	6 points for sure	Option X ◯ ◯ Option Y
7	unknown prize	7 points for sure	Option X ◯ ◯ Option Y
8	unknown prize	8 points for sure	Option X ◯ ◯ Option Y
9	unknown prize	9 points for sure	Option X ◯ ◯ Option Y
10	unknown prize	10 points for sure	Option X ◯ ◯ Option Y

[20] This task was only used in the second sessions of experiments, see section 6.3. These sessions consisted of risk task 2, ambiguity task 1, uncertainty task 1, and uncertainty task 3 only.

Appendix D: Non-parametric preference measures

This appendix describes the calculation of the non-parametric measures of uncertainty, risk, and ambiguity aversion obtained from the tasks as presented in section 5.
In all tasks, the switching point from one option to another indicates a subject's indifference between both options. This allows constructing non-parametric preference measure by linearly mapping the indifference point into an interval between 0 and 1. A value of 0 corresponds to extreme uncertainty (risk/ambiguity) seeking preferences, while a number of 1 means extreme uncertainty (risk/ambiguity) aversion. A value of 0.5 implies uncertainty (risk/ambiguity) neutrality.

Uncertainty tasks: Under the assumption of risk and ambiguity neutrality, a subject is indifferent in situation 5 (for all uncertainty tasks) since the expected value of both options are identical. Indifference at situation 5 hence corresponds to uncertainty neutrality.
For uncertainty tasks 2 and 3, if a subject prefers in situation 0 a certain payoff of 0 points over an uncertain payoff which can be at worst 0 points, this corresponds to extreme uncertainty aversion and is assigned an uncertainty aversion measure of 1. If a subject prefers in situation 10 an uncertain payoff which can be at best 10 points over a certain payoff of 10 points, this corresponds to extreme uncertainty seeking preferences and is assigned an uncertainty aversion measure of 0. Uncertainty task 1 follows the same logic. For all other switching points the uncertainty aversion measure is obtained by linear interpolation, using the mid-point around the switching point:

$$1 - \frac{\text{mid-point of earnings of risky/safe option}}{10}$$

For example, a switch between situations 5 and 6 implies an uncertainty aversion measure of 0.45 (in all 3 uncertainty tasks).

Risk tasks: Under the assumption of risk neutrality a decision maker evaluates both options according to their expected value. In this case, a subject is indifferent in situation 6 for risk task 1, and in situation 8 in risk task 2 since the expected values of both options are identical.
In risk task 1, a preference for box B in situation 1 corresponds to extreme risk seeking preferences, while a preference for box A in situation 10 is interpreted as extreme risk averse preferences. Hence, the risk aversion measure is calculated as the mid-point of the probability of winning 10 points in box B around the switching point. For example, a switch between situations 6 and 7 implies a risk aversion measure of 0.55.
In risk task 2, a preference for option 2 in situation 1 corresponds to extreme risk averse preferences, while a preference for option 1 in situation 14 corresponds to extreme risk seeking preferences. In this task, the risk aversion measure is calculated as:

$$1 - \frac{\text{mid-point of sure payment}}{20}$$

For example, a switch between situations 2 and 3 implies a risk aversion measure of 0.775.

Ambiguity tasks: Under the assumption of ambiguity neutrality, a subject is indifferent in situation 5 for ambiguity task 1, and in situation 7 for ambiguity task 2.
In ambiguity task 1, a preference for box 1 in situation 0 corresponds to extreme ambiguity averse preferences, while a preference for box 2 in situation 10 is corresponds to extreme ambiguity seeking preferences. In ambiguity task 2, a preference for box Y in situation 0 corresponds to extreme ambiguity seeking preferences, while a preference for box X in situation 14 is corresponds to extreme ambiguity averse preferences.
The ambiguity measures are derived from the matching probabilities that are consistent with the subject's switching points. For example, in ambiguity task 1, a switch between situations 2 and 3 corresponds to a matching probability m of 0.25. Hence, the ambiguity aversion measure is 1-m = 0.75.