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Lotto lotteries — Decision making under uncertainty when payoffs are unknown

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ABSTRACT

This paper analyses decision making under uncertainty when payoffs are unknown, similar to a Lotto lottery. In a Lotto lottery, the probability of winning a prize is known, but the size of the prize is unknown. This paper 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. Then the paper empirically analyses human behaviour when uncertainty can be described as a Lotto lottery. There is considerable heterogeneity in the subjects' aversion to lotteries with unknown payoffs. Further analysis shows that choices of decision makers can be best explained by a combination of risk and ambiguity preferences. These results suggest that subjects treat unknown payoffs similar to known payoffs with ambiguous probabilities.

1. Introduction

Economists usually distinguish between two types of lotteries to describe 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 a roulette lottery is modelled using Expected Utility Theory (von Neumann & Morgenstern, 1944), while decisions under uncertainty of horse lotteries are modelled using Subjective Expected Utility Theory (Anscombe & Aumann, 1963; Savage, 1954).

Yet, many situations in everyday life do not correspond to either group: situations where the probability of some payoff is 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: 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 side effects are fairly well-known in advance. Yet, the severities of the side effects are rather unknown (Budescu & 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 (i.e., the actual policy implemented) is rather unknown.[1]

The objective of this paper is to gain a better understanding of 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.

The first main contribution of this study is to introduce a utility-based framework to model decision making if uncertainty can be described as a Lotto lottery. This model formalizes and extends some earlier ideas first proposed by Camerer and Weber (1992) to model decision making involving unknown payoffs. The model is inspired by the Anscombe and Aumann (1963) model of subjective expected utility theory. Preferences over Lotto lotteries are modelled as two-stage compound lotteries. The first stage involves a roulette lottery over different states of the world, determining whether a payoff is obtained. The second stage consists of a horse lottery, assigning subjective probabilities to a set of potential payoffs, given some state of the world is realized. In this set-up, unknown payoffs are thus captured by a set of as known payoffs with unknown probabilities, and can be modelled by subjective expected utility.

However, since the seminal work of Ellsberg (1961) we know that when confronted with lotteries with unknown probabilities, decision makers often fail to attribute a unique subjective probability to each

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[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 Budescu and Templin (2008).

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of the possible outcomes, but treating them as ambiguous. In one of his thought experiments, a decision maker can draw a ball from an urn that contains red, black and yellow balls. If a black ball is drawn there is a payoff of 100, but nothing otherwise. The decision maker knows the probability of drawing a red ball (a third), and the joint probability of drawing a black or a yellow ball (two thirds). This set-up can be reinterpreted as a two-stage Lotto lottery: the first stage determines whether there might be a prize (an ambiguous lottery with a yellow or black ball) or not (red ball). In this stage, the probabilities are given (2/3 versus 1/3). If the ambiguous lottery is selected, the second stage then determines whether there is a prize of 100 or zero. In this stage, the probabilities are unknown.

These considerations mean that choices over Lotto lotteries should to some extent be shaped by preferences over ambiguous probabilities as well. Against this backdrop, the compound lottery model is extended to allow for ambiguity (and attitudes towards ambiguity) in the second-stage horse lotteries.

The second main contribution of the paper is to empirically analyse decision making when confronted with unknown payoffs using this new parametric utility-based framework. Different to previous work (Du & Budescu, 2005), this study also allows for a finer measurement of the subjects' attitude towards unknown payoffs, and thus a better analysis of the factors driving preferences over unknown payoffs.

Using an experimental set-up inspired by the Ellsberg (1961) three-colour urn experiment, I examine a decision maker's attitude towards lotteries with unknown payoffs relative to lotteries with known payoffs. There is considerable heterogeneity in the subjects' aversion to lotteries with unknown payoffs, i.e., the preference for lotteries with known payoffs over lotteries with unknown payoffs.

Finally I examine the underlying reason for cross-sectional differences in the subjects' aversion to unknown payoffs. The results show that both risk and ambiguity preferences are important to explain the subjects' behaviour when facing Lotto lotteries. In direct comparison, risk preferences are more related to aversion to unknown payoffs than ambiguity preferences. Yet, this nevertheless means that subjects are not fully confident in the subjective probabilities they assign to each of the payoffs, but perceive them ambiguous, as conjectured.

In a last step, the paper considers the case where the unknown payoff can lie within a continuous range rather than being limited to a small countable set. This is conceptually closer to the general notion of Lotto lotteries in everyday life. The results suggest that subjects treat a continuous payoff space similar to a discrete set of payoffs. As before, both risk and ambiguity preferences can explain the subjects' choices when faced with Lotto lotteries. Hence, although the compound lottery model expresses unknown payoffs as a countable set of known payoffs with unknown probabilities, it seems to be capturing behaviour when faced with completely unknown payoffs equally well. Essentially, decision makers seem to apply the same decision heuristics as if the set of potential payoffs was limited to a small set.

Despite their relevance, there is little theoretical and experimental literature on preferences over Lotto lotteries. Schoemaker Paul (1989) is the first to develop a framework similar to a Lotto lottery. Different from this paper, Schoemaker Paul (1989) assumes that decision makers have objective information about the probabilities for each of the possible prizes. The compound lottery can therefore be reduced to a simple lottery, and analysed using expected utility theory.

Camerer and Weber (1992) discuss the situation when payoffs of lotteries are left unspecified, or "ambiguous".[2] They argue that decision makers will assign subjective probabilities to each of the possible outcomes. They conclude that choices over Lotto lotteries should be perfectly explained by subjective expected utility, and hence risk preferences only.

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 2.4. While interesting from a theoretical point of view, these models are difficult to take to the data. The compound lottery model proposed in this paper offers such a framework. Essentially, it extends the ideas outlined in Camerer and Weber (1992) by allowing subjective probabilities for known payoffs to be ambiguous.

This paper builds on 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 & 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 unknown outcomes and unknown probabilities on human decision making. While these studies recognize that unknown payoffs can be reinterpreted as known payoffs with unknown probabilities, they stress that is it important to differentiate between unknown probability and unknown payoff to understand how people react to different types of "vague" information.

These studies present mixed evidence on attitudes towards gambles with unknown payoffs. In his review, Onay et al. (2013) shows that these attitudes depend on the elicitation method, and whether the unknown outcome involves gains or losses. While Budescu et al. (2002), Du and Budescu (2005), Budescu and Templin (2008) and Onay et al. (2013) find that the majority of subjects have a preference for unknown payoffs in the gain domain, Gonzáles-Vallejo et al. (1996), Ho et al. (2002) and Eliaz and Ortoleva (2016) show that subjects are averse to unknown payoffs, 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" (Budescu et al., 2002; Kuhn et al., 1999).[3]

While these empirical studies allow for a first understanding of decision making under uncertainty if payoffs are unknown, they are subject to a number of shortcomings. Most allow only for a binary differentiation between preferences against or in favour of unknown payoffs. Furthermore, these studies 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 implied by Camerer and Weber (1992), ambiguity aversion, or both. The Lotto tasks to measure individual attitudes towards unknown payoffs in this study allow for a much finer measurement of the subjects' preferences.

The remainder of this paper is organized as follows. The next section introduces the concept of Lotto lotteries using a simplified example. Section 3 presents the experimental design. The results of the experimental sessions are presented in Section 4. Sections 5 and 6 show that preferences over Lotto lotteries can be explained by a combination of risk and ambiguity preferences. Section 7 offers some concluding remarks.

2. Theoretical considerations

2.1. Introductory example

Consider a simplified version of the standard state Lottery. Suppose a decision maker has the choice between drawing a ball from one of two urns, urn F and urn G (Table 1). Both urns contain two balls, one

[2] This paper uses the term "unknown payoff" to avoid confusion with the literature that uses the term "ambiguity" to denote unknown probabilities.

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

Table 1
Lotto lotteries (urns F and G).

Type of ball (state of the world s)	Probability p_s	Colour	Payoff x
coloured	0.5	red	1
		yellow	3
white	0.5	white	0

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 3. There is no payoff 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 unknown. All that is known is that the payoff may be 1 or 3.

Standard expected utility cannot model preferences over the two gambles, since it requires 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 $\{0, 1, 3\}$, 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 lottery as compound lottery

Lotto lotteries can be modelled as compound lotteries. The first stage determines whether a prize is drawn, using an objective probability. The second stage determines the amount of the prize. Schoemaker Paul (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.

In the framework considered in this paper, there is no objectively given probability distribution over prizes. If the probability distribution over the prizes in the second stage is left unspecified, the decision maker's preferences over Lotto lotteries can be modelled using some subjective probability distribution. This allows to derive again a reduced lottery, and apply subjective expected utility.

2.2.1. Compound lottery model

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

$$\sum_{s\in\mathcal{S}} p_s = 1, p_s \geq 0 \quad \forall s$$

Put differently, there is a roulette lottery over all possible states. States are observable ex-post. Furthermore, there is a set $\mathcal{X}$ of x possible payoffs. This is final payoff for the decision maker. Then define a set C of c possible scenarios. Mathematically, scenarios are functions from states into payoffs, $C : \mathcal{S} \to \mathcal{X}$. A scenario specifies for each state $s \in \mathcal{S}$ a payoff $x \in \mathcal{X}$.[4] Finally, a bet B is a list of subjective probabilities for each of the scenarios, such that

$$\sum_{c\in C} \mu_c(B) = 1, \mu_c(B) \geq 0 \quad \forall c$$

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

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

[4] Savage (1954) uses the term "acts".

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.

The compound lottery model formalizes the ideas of Camerer and Weber (1992). They argue that when payoffs of lotteries are unspecified, decision makers will assign subjective probabilities to each of the possible outcomes. They conclude that choices over Lotto lotteries should be perfectly explained by subjective expected utility, and hence risk preferences only.

2.2.2. Example as compound lottery

In the introductory example, the state of the world is the outcome of the draw, i.e., $\mathcal{S} = \{coloured, white\}$. The probability for each state to occur is known, $p_c = p_w = 0.5$. The set of payoffs is $\mathcal{X} = \{0, 1, 3\}$. There are 2 scenarios for each urn: either the coloured ball is red or yellow. Hence, the set C of c possible scenarios is given by

$$c_{yellow} = (3, 0) \text{ and}$$
$$c_{red} = (1, 0),$$

where the first number gives the payoff if $s = coloured$, and the second number gives the payoff if $s = white$. However, the decision maker does not know which scenario corresponds to the true scenario. Finally, there are two bets, F and G with subjective probabilities μ^F and μ^G for the first scenario:

$$\text{coloured ball in urn F} = \begin{cases} yellow(x^F = 3) & \text{with probability } \mu^F \\ red(x^F = 1) & \text{with probability } 1 - \mu^F \end{cases}$$

$$\text{coloured ball in urn G} = \begin{cases} yellow(x^G = 3) & \text{with probability } \mu^G \\ red(x^G = 1) & \text{with probability } 1 - \mu^G \end{cases}$$

The preference of drawing a ball from F or G then depends on the subjective probabilities μ^F and μ^G. The expected utilities of gambles F and G are:

$$U(F) = 0.5\left(u(3)\mu^F + u(1)(1-\mu^F)\right) + 0.5 \cdot u(0)$$
$$U(G) = 0.5\left(u(3)\mu^G + u(1)(1-\mu^G)\right) + 0.5 \cdot u(0)$$

From this it follows:

$$F \succ G \Leftrightarrow$$
$$U(F) > U(G) \Leftrightarrow$$
$$(u(3) - u(1))\,\mu^F > (u(3) - u(1))\,\mu^G$$

As long as $u(3) > u(1)$, it follows $\mu^F > \mu^G$. For any increasing utility function over payoffs, the decision maker will select the urn where she attributes a higher probability of drawing a yellow ball (a payoff of $x = 3$).

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 is not 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., C^F and C^G.

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

Table 2
Roulette lottery (urn H).

Type of ball (state of the world s)	Probability p_s	Colour	Payoff x
white	0.5	white	0
coloured	0.5	blue	2

2.3. Lotto lottery as ambiguous lottery

Another possibility is to model Lotto lotteries as three-colour (Ellsberg, 1961) urns. In one of his thought experiments, a decision maker can draw a ball from an urn that contains red, black and yellow balls. If a black ball is drawn there is a payoff of 100, but nothing otherwise. The decision maker knows the probability of drawing a red ball (a third), and the joint probability of drawing a black or a yellow ball (two thirds).

Lotto lotteries can be reinterpreted as three-colour (Ellsberg, 1961) urns. The decision maker knows the probability of winning a prize (black or yellow ball, probability of two thirds), and the probability of not winning a prize (red ball, probability of a third). This corresponds to the first stage of the compound lottery. Yet, the probabilities of winning a high prize (black ball, payoff 100) or a low prize (yellow ball, payoff 0) are unknown. This is the second stage of the compound lottery.

The key insight of Ellsberg (1961) is that when confronted with lotteries with unknown probabilities (i.e., there is ambiguity about probabilities), decision makers often fail to attribute a unique subjective probability to each of the possible outcomes. Thus, their behaviour cannot be explained using subjective expected utility theory. As a result, a variety of models have been proposed that extend the expected utility model to allow for ambiguity (Gilboa & Schmeidler, 1989; Schmeidler, 1989). In these models, decision making with unknown probabilities can be explained by ambiguity preferences.

2.3.1. Lotto lotteries versus roulette lotteries

These considerations mean that choices over Lotto lotteries should to some extent be shaped by ambiguity preferences. To see this, consider another thought experiment. Suppose a decision maker has the choice between drawing a ball from one of two urns, urn F and urn H. Urn F is a Lotto lottery, as before. This requires the decision maker to attribute subjective probabilities for the coloured ball being either red or yellow. In contrast, the coloured ball in urn H is known to be blue, and provides a payoff of 2. Thus, urn H is a roulette lottery with known probabilities for each payoff (Table 2).

An expected choice in this thought experiment is to prefer urn H over urn F, i.e., a preference for the roulette lottery over the Lotto lottery. Such a choice can be rationalized by the subject's risk preferences, as suggested by Camerer and Weber (1992). Assuming that the decision maker has symmetric subjective probabilities for high and low prizes in the Lotto lottery, risk aversion implies a higher subjective expected utility of the roulette lottery relative to the Lotto lottery.

However, in practice, decision makers might find it difficult to attribute precise subjective probabilities to each of the scenarios in the Lotto lottery. If a decision maker is not sure about the probabilities of the high and low prize, he might consider a range of probabilities possible, i.e., he perceives them ambiguous — similar to Ellsberg's three-colour urn experiment. If the decision maker is ambiguity averse, he will prefer the roulette lottery over the Lotto lottery, even if he is risk neutral.

To conclude, there are two possible explanations for the same observed behaviour: risk and ambiguity preferences.

2.3.2. Compound lottery model with ambiguity

Following these insights, the compound lottery model (1) introduced in Section 2.2 is extended to allow for ambiguity in the second-stage horse lotteries. Following Ahn et al. (2014), this paper uses the α-MEU utility model by Ghiradato et al. (2004) to incorporate ambiguity preferences. Then the expected utility of a bet B is given as

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

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.

Appendix A presents a simple numerical illustration how both risk and ambiguity preferences can explain the preference of roulette lotteries over Lotto lotteries.

2.4. Related theoretical models

The compound lottery model is not the only possibility to formalize the idea of Lotto lotteries. The literature has proposed a variety of models to analyse decision making under uncertainty when there is not a clear mapping between probabilities and payoffs.

For example, preferences over Lotto lotteries can be modelled using belief and plausibility functions following Dempster (1967) and Shafer (1976).[5] 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 3 (yellow ball), however, they differ: Their lower bound is given by a 0% probability, $Bel(1) = Bel(3) = 0$, while their upper bound is given by a 50% probability, $Pl(1) = Pl(3) = 0.5$.

Preferences over Lotto lotteries can hence be conceived as preferences over belief or plausibility functions. Lotto lotteries can therefore be evaluated using Choquet expected utility (Gilboa, 1987; Schmeidler, 1989), where the capacity is structured as a belief function. Thus, the unknown outcomes of Lotto lotteries directly translate into probabilistic ambiguity about the set of possible outcomes.

These ideas have been formalized, 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 a 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-MEU model used 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

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

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.

While these models provide valuable theoretical insights, it is not straightforward to take them to the experimental data. The two-stage compound lottery model presented in this paper offers a framework to better understand decision making if payoffs are unknown. At the same time, it provides a convenient set-up to empirically disentangle the effects of risk and ambiguity preferences on decision makers' aversion to unknown payoffs.

3. Experimental design

3.1. Research design

The objective of the empirical part of this study is to obtain a better understanding of decision making under uncertainty when payoffs are unknown. Most important, the paper analyses the role of both risk and ambiguity preferences for decisions involving Lotto lotteries.

In a first step, I measure the subjects' 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 unknown payoffs. In the second step, I aim at explaining the subjects' observed choices. As discussed in Section 2.3.1, both individual risk and ambiguity preferences might have an influence on decision tasks with unknown payoffs.

It is well-known that preference measures obtained from incentivized choice tasks are often subject to considerable measurement errors (Parez et al., 2021). To reduce measurement errors when eliciting the subjects' aversion to unknown payoffs, risk aversion, and ambiguity aversion, this study follows Falk et al. (2023) and asks subjects to participate in two choice tasks for a given preference. The baseline preference measure is then obtained by averaging the results of the two tasks, a technique aiming at reducing measurement errors (Wang & Navarro-Martinez, 2023).

All tasks are reproduced in Appendix B; screenshots are presented in the online appendix.

3.2. Aversion to unknown payoffs

The tasks to measure a subject's aversion to lotteries with unknown payoffs build on the thought experiment presented in Section 2.3.1.

Lotto task 1 measures aversion to unknown payoffs by eliciting a risk equivalent to a Lotto lottery, i.e., a roulette lottery that makes decision makers indifferent between the Lotto lottery and the roulette 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 situation, 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 averse to unknown payoffs.

The lotteries are implemented using two boxes filled with balls of different colours.[6] 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) 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.

Lotto task 2 is a simplified version of Lotto task 1, dropping the white balls from both boxes. It thus elicits a certainty equivalent of an unknown prize. 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 Lotto task 1, subjects are expected to prefer option B (with unknown payoff) in the first situation over option A (a sure payoff of 0 points). However, since option A is getting more attractive from situation to situation, subjects are expected to switch to option A at some point. The earlier they switch, the more they are averse to unknown payoffs.

When measuring aversion to unknown payoffs, and – more important – when trying to explain the subjects' aversion to unknown payoffs by risk and ambiguity preferences, it is important to rule out that subjects form asymmetric subjective probabilities μ_c for the prizes of the Lotto lotteries. To see this, consider a decision maker believing that the probability of a low prize is very high. Then the (subjective) expected value of the Lotto lottery is lower than the expected value of the roulette lottery. In this case, even risk- and ambiguity-neutral decision makers would rationally reject the Lotto lotteries.

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 for a low prize (Charness et al., 2013; Chow & Sarin, 2002).

To avoid such non-symmetric beliefs, participants are asked to select the colour of the ball that entitles them to a high prize in the unknown option (box J and option B) before the draw. The drawback of this mechanism is that it restricts the number of possible prizes in the Lotto lotteries. To keep the Lotto tasks simple, they allow only for two different prizes, one of which being zero.[7] Section 6 introduces a Lotto task where the unknown payoffs can lie in a continuous range, i.e., there is an uncountable set of prizes.

3.3. Risk and ambiguity preferences

To measure risk and ambiguity preferences, this study uses established choice lists taken from the literature.

Risk task 1 measures risk preferences by eliciting a risk equivalent for a sequence of roulette lotteries. The task is a simplified version of the Holt and Laury (2002) design, and 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, 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.

Risk task 2 determines risk preferences by eliciting a certainty equivalent of 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

[6] 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" used in the economics literature.

[7] The mechanism to ensure symmetric beliefs by asking participants to match ball colours to prizes before the draw requires setting a different colour for each prize. While it is possible to offer more than two prizes, the mechanism becomes quickly impractical when increasing the number of prizes beyond a small countable set.

proceeds, the lottery remains identical while the safe payment increases monotonically. The point at which subjects switch from the lottery to the safe payment reveals the subjects' risk preferences.

Ambiguity task 1 determines ambiguity preferences by eliciting a matching probability of an ambiguous lottery. A matching probability is a risk equivalent of an ambiguous lottery, i.e., the probability of a risky lottery at which a subject is indifferent between a risky and the ambiguous lottery.

The task is based on the two-colour thought experiment by Ellsberg (1961), and is taken from Cavatorta and Schröder (2019). The task involves 11 sequential decisions between a risky and an ambiguous lottery. The composition and payoff structure of the ambiguous lottery is identical in all 11 situations, offering a fixed prize with unknown probability. In contrast, the risky lottery changes from one situation to the next. More precisely, the probability of winning the (same) fixed prize monotonically increases as the task proceeds, thereby increasing the expected payoff of the risky lottery.

The point at which subjects switch from preferring the ambiguous lottery to the risky lottery reveals their ambiguity preferences. The risky lottery is equally attractive as the ambiguous lottery, but no longer ambiguous. Hence, this task allows measuring the degree subjects are averse to the absence of probabilities (i.e., ambiguity), independent of the subject's utility function, and thus risk preferences (Dimmock et al., 2015).

Ambiguity task 2 is a variant of ambiguity task 1, also determining ambiguity preferences by eliciting a matching probability of 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 is restricted to be either 0% or 100% (instead of allowing for any probability).

In both ambiguity tasks, participants were asked to select the colour of the winning ball in the ambiguous box, similar to the Lotto tasks. This procedure ensures that participants have no reason to form asymmetric beliefs about the composition of the ambiguous box.[8]

3.4. 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 preferences, and concluded with the tasks to measure aversion to unknown payoffs. In a second round of experiments (see Section 6) the sequence of tasks was reversed, but no order effects are observed.

The payment modality of the incentivized tasks 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.[9]

Earnings from the tasks were calculated in terms of points, and then converted at a rate of 5:1 into GBP. Earnings were paid in private at the end of the sessions. On average, subjects earned GBP 11, which includes a fixed show-up fee of GBP 2. The lowest payment was GBP 4, the highest payment GBP 16. Since the sessions lasted for about 60 min, the payoffs are substantial.

4. Empirical results

4.1. Aversion to unknown payoffs

In binary choice lists, the standard pattern is a threshold strategy. Since the relative attractiveness of the two options changes monotonically as the list proceeds, subjects tend to prefer one option over the other up to a switching point. In both Lotto tasks, the natural choice is to first select the Lotto lottery with unknown payoffs, and then switch to the roulette lottery (Lotto task 1) or the safe payment (Lotto task 2). Yet, some subjects switch more than once – a behaviour difficult to reconcile with rational choice. There are 9 multiple switchers in the Lotto task 1 (10% of the sample) and 7 multiple switchers in the Lotto task 2 (8%).[10] In case a subject has multiple switching points, I follow Falk et al. (2023) and define a subject's switching point as her average switching point.[11]

Fig. 1 presents the distribution of switching points in the two Lotto tasks. Most subjects switch close to the midpoint of possible switching points. Yet, there a few subjects switch rather early (indicating a strong aversion to unknown payoffs), while some others switch rather late (indicating a preference for unknown payoffs).

The switching point indicates a subject's indifference between the two options. This allows constructing non-parametric measures of aversion to unknown payoffs by linearly mapping the indifference points into an interval between 0 and 1. A value of 0 corresponds to an extreme liking of unknown payoffs, while a number of 1 means extreme aversion to unknown payoffs. A value of 0.5 implies neutrality (for more details, see Appendix C). To reduce the impact of potential measurement errors, the final preference measure is obtained by averaging the results of the two tasks, as discussed earlier.

Panel A of Table 3 shows that subjects are slightly averse to unknown payoffs (> 0.5) in both tasks, on average. Using a t-test, these averages are however not statistically different from 0.5. The finding of no significant aversion to unknown payoffs is in line with the inconclusive results in the experimental psychology literature, which documents evidence for both aversion and liking of unknown payoffs in the gain domain (see the introduction). Averaging the measures obtained from the two tasks reduces the variance of aversion to unknown payoffs significantly, suggesting that this measure allows to correct for outliers caused by measurement errors, indeed. In the remainder of the analysis, the paper thus predominantly relies on the combined measure (baseline). Since Lotto task 2 has fewer multiple switchers (which can be interpreted that the task is easier to understand) and a lower variance, this measure might be more reliable and is hence used as robustness specification.

Panel B reports the correlation statistics between the various measures. All measures are significantly related to each other, especially when using the Spearman (1904) correlation coefficient as measure of association. This suggests that subjects are consistent across the two choice tasks.

[8] Since there is no information on the composition of the ambiguous lottery, the literature Butler et al. (2014), Dimmock et al. (2015), Lauriola and Levin (2001) assumes that subjects consider the full range of probabilities possible. In other words, because of the design of the task, we can rule out subjects to form a unique subjective probability distribution for the composition of the ambiguous lottery.

[9] 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.

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

[11] For some descriptive statistics of multiple switching points, see Appendix D.1. Despite being exposed to control questions before each choice task, multiple switching points might indicate a lack of understanding of the tasks, resulting in measurement errors. However, Appendix D.2. shows that excluding subjects with multiple switching points from the sample does not change the results.

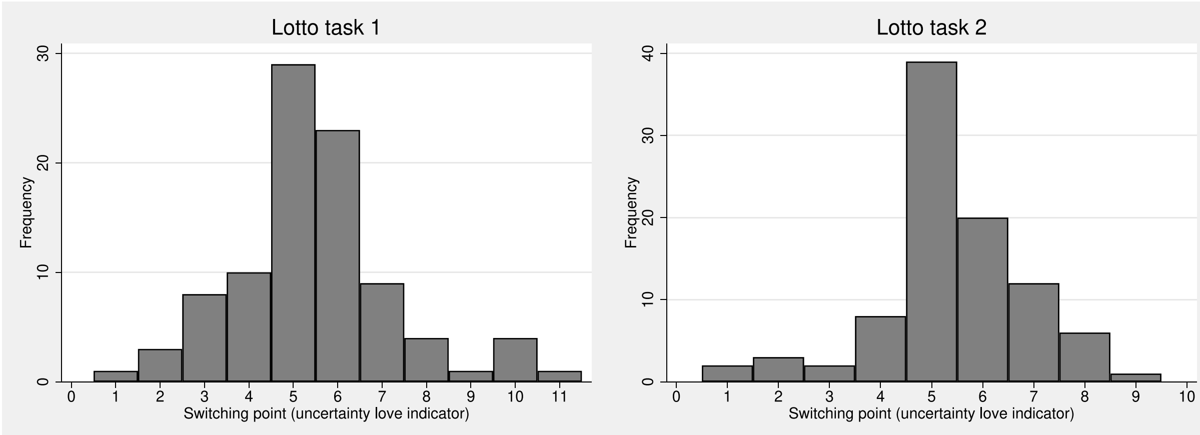

Fig. 1. Switching points in Lotto tasks. This graph presents the distribution of switching points in the two Lotto tasks.

Table 3
Descriptive statistics — aversion to unknown payoffs.

Panel A: Non-parametric measures of aversion to unknown payoffs					
	Observations	Mean	Standard deviation	Lowest	Highest
Lotto task 1	93	0.503	0.182	0.00	0.95
Lotto task 2	93	0.510	0.147	0.15	0.95
Combined measure	93	0.507	0.127	0.20	0.90

Panel B: Correlation statistics			
	Lotto task 1	Lotto task 2	Combined measure
Lotto task 1		0.282***	0.792***
Lotto task 2	0.182*		0.768***
Combined measure	0.823***	0.708***	

The table summarizes the results of the two Lotto tasks. Panel A reports the non-parametric measures of aversion to unknown payoffs derived from the switching points. Panel B reports the correlation statistics between the 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 3.2 and appendices B and C.

4.2. Risk and ambiguity aversion

Table 4 presents the results from the risk tasks. Similar to the Lotto 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 as their average switching point.

The switching points allow deriving non-parametric measures of risk aversion (see Appendix C), where a value of 1 corresponds to extreme risk aversion, a value of 0 means extreme risk seeking preferences, and a value of 0.5 implies risk neutrality. To reduce the impact of potential measurement errors, the final risk aversion measure is obtained by averaging the results of the two tasks.

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

The switching points also allow to infer the subjects' coefficient of relative risk aversion (CRRA). Since the switching points indicate a decision maker's indifference between the two options, the expected utility of both options should be equal. Using the CRRA utility function $u(x) = x^{1-\gamma}$, where γ is the CRRA parameter, it is possible to derive the value of γ that is consistent with the subjects' observed switching points (Andersen et al., 2008). Mathematically, this means finding the value of γ such that both options have the same expected utility. Panel B of Table 4 presents the CRRAs, where a positive value corresponds to risk aversion. While the average CRRA derived from 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 risk preferences. The risk measures obtained from both tasks are not significantly related to each other. Put differently, subjects do not seem to behave consistently across the two tasks. While surprising, this is a common finding in the literature, likely caused by differences in the framing of the tasks (Friedman et al., 2022). To some extent, this also might indicate some measurement error due to random switching points (Vieider, 2018). This observation is another reason why the baseline specification uses the combined measure of risk aversion, thereby reducing the impact of measurement errors.

Table 5 presents the results of the ambiguity tasks. As before, most subjects adopt a threshold strategy with a single switching point. 10 subjects (11%) have multiple switches in ambiguity task 1, while 13 subjects (14%) have multiple switches in ambiguity task 2.

Similar to the risk tasks, the switching point in the ambiguity tasks indicate a decision maker's indifference between the two options available. Since the set of possible payoffs is identical in both options (0 or 10 points), choices do not depend on risk preferences, and ambiguity preferences are fully captured by the probability that makes the risky option equally attractive as the ambiguous option (Dimmock et al., 2015). This matching probability m is defined as the mid-point of the probabilities to win a prize in the risky option around the switching

Table 4
Descriptive statistics — risk aversion.

Panel A: Non-parametric risk aversion measures					
	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 measure	93	0.549***	0.102	0.25	0.95
Panel B: Coefficients 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 measure	93	0.009	0.719	−6.34	0.85

Panel C: Correlation statistics — non-parametric measures			
	Risk task 1	Risk task 2	Combined measure
Risk task 1		0.032	0.689***
Risk task 2	0.083		0.676***
Combined measure	0.700***	0.773***	
Panel D: Correlation statistics — coefficients of relative risk aversion			
	Risk task 1	Risk task 2	Combined measure
Risk task 1		0.032	0.741***
Risk task 2	0.077		0.617***
Combined measure	0.326***	0.968***	

The table summarizes the results of the two risk tasks. Panel A reports the non-parametric risk aversion measures derived from the switching points. Significance of the difference to 0.5 is estimated using a t-test. Panel B reports the coefficients of relative risk aversion (γ) implied by the switching points. Significance of the difference to 0 is estimated using a t-test. 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 3.3 and appendices B and C.

Table 5
Descriptive statistics — ambiguity aversion.

Panel A: Ambiguity aversion parameters (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 measure	93	0.534***	0.064	0.36	0.70

Panel B: Correlation statistics			
	Ambiguity task 1	Ambiguity task 2	Combined measure
Ambiguity task 1		0.088	0.706***
Ambiguity task 2	0.069		0.711***
Combined measure	0.702***	0.759 ***	

The table summarizes the results of the two ambiguity tasks. Panel A reports the ambiguity aversion 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 aversion 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 3.3 and appendices B and C.

point. I then define the ambiguity aversion parameter as 1 less the matching probability.

A value of 1 corresponds to extreme ambiguity aversion, while a value of 0 means extreme ambiguity seeking preferences. A parameter value of 0.5 implies ambiguity neutrality (see Appendix C). 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 combined 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 reduces the variance of the ambiguity aversion measure, 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). Since ambiguity task 1 has fewer multiple switchers, this measure of ambiguity aversion is used in the robustness specification. Similar to the risk preferences, panel C shows that the ambiguity preference measures obtained from the two tasks are not related to each other, i.e., there seems to be a low within-subject consistency. This finding stresses again the importance of using the combined ambiguity aversion measure in the baseline specification to reduce the impact of measurement errors.

5. Explaining aversion to unknown payoffs

This section explores the underlying reason for cross-sectional differences in the subjects' aversion to unknown payoffs. The evaluation 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 (i.e., ambiguity preferences).

5.1. Analysis of non-parametric preference measures

This section analyses the subjects' aversion to unknown payoffs using the non-parametric preference measures. This analysis is carried out for both the baseline specification using the combined preference measures, as well as the robustness specification which uses the non-parametric measures obtained from the tasks with the lowest number of multiple switchers.

Panels A and B of Table 6 show that the subjects' aversion to unknown payoffs is significantly related to both risk and ambiguity preferences. In direct comparison, the correlation with risk aversion is higher than the correlation with ambiguity aversion. The correlation between risk and ambiguity preferences is considerably lower, even being not significant in the baseline specification.

Panels C and D report the coefficient estimates of OLS regressions of the subjects' aversion to unknown payoffs on risk and ambiguity preferences,

$$lotto_i = \delta + \beta_r risk_i + \beta_a amb_i + \varepsilon_i, \tag{3}$$

where $lotto_i$ denotes the non-parametric measure of aversion to unknown payoffs, $risk_i$ is the non-parametric measure of risk aversion, amb_i is the non-parametric measure of ambiguity aversion, and ε_i is the error term.

Risk preferences can explain some of the observed behaviour in the Lotto tasks. In both specifications, the risk aversion coefficients are significantly different from zero, at high confidence levels (see the first column of both panels). In addition, the explained variance of aversion to unknown payoffs is substantial, reaching up to 39% in the robustness specification. Hence, there is a strong support for the hypothesis that subjects behave according to subjective expected utility.

However, the table shows that the ambiguity aversion coefficients are also highly significant (second column). While in comparison to the risk-based explanation the explained variance is lower, this result nevertheless suggests that subjects are not fully confident about the subjective probabilities they attribute to the payoffs, and hence consider them partly ambiguous. The pure risk-model cannot capture such behaviour.

This observation is confirmed when using both risk and ambiguity preferences to predict the subjects' aversion to unknown payoffs (third column). 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 subjects' choices.[12]

5.2. Predicting switching points

This section uses the compound lottery model with ambiguity, as presented in Section 2.3.2, to predict the subjects' switching points in the Lotto tasks, and then compares them to their actual, observed switching points. Ambiguity preferences are thus captured by the α-MEU utility model (Ghiradato et al., 2004). As Bernoulli utility function, I use the constant relative risk aversion (power) utility.

For each subject, I use the risk (γ) and ambiguity (α) utility parameters obtained from the subjects' switching points, see Section 4.2. Then I calculate the expected utility of all options presented in the Lotto tasks. In each situation, the option with the highest expected utility is selected. This allows predicting a switching point between the two options, based on the subject's risk and ambiguity preferences.

The table presents the analysis of aversion to unknown payoffs based on the non-parametric preference measures. Panels A and B report the correlation statistics between the non-parametric preference measures. The lower part of the panel presents the Pearson correlation, the upper part the Spearman correlation. Panels C and D report the coefficient estimates of OLS regressions of the non-parametric preference measures of aversion to unknown payoffs on risk and ambiguity preferences,

$$lotto_i = \delta + \beta_r risk_i + \beta_a amb_i + \varepsilon_i, \tag{3}$$

where $lotto_i$ denotes the non-parametric measure of aversion to unknown payoffs, $risk_i$ is the non-parametric measure of risk aversion, amb_i is the non-parametric measure of ambiguity aversion, and ε_i is the error term. p-values are given in parenthesis below the coefficient estimates.

Panels A and C report the results using the combined preference measures (the baseline specification). Panels B and D report the results using the measures obtained from Lotto task 2, risk task 2, and ambiguity task 1 (the robustness specification). *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Starting with Lotto task 2, the utility of the safe option (the degenerate roulette lottery) with a payoff $x \in [0, 10]$ is given as[13]

$$u(x) = \frac{x^{(1-\gamma)}}{1-\gamma}. \tag{4}$$

In case of risk-neutrality ($\gamma = 0$), the utility function simplifies to $u(x) = x$. The expected utility of the unknown payoff in the Lotto lottery is

$$\alpha - MEU(10) = \alpha\, u(0) + (1-\alpha)u(10) = (1-\alpha)\, \frac{10^{(1-\gamma)}}{1-\gamma}. \tag{5}$$

In this two-dimensional state space, $\alpha = 0.5$ corresponds to ambiguity neutrality. Ambiguity neutrality reflects the fact that 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).[14] Since Lotto task 1 is identical to Lotto task 2 other than adding the possibility of winning no prize with a probability of 50%, the predicted switching point for Lotto tasks 2 (and the combined measure) can be calculated using the same formulas.

Table 7 reports the results of an OLS regression of the observed switching points ($switch_i^o$) in the Lotto tasks on the predicted switching points ($switch_i^p$) implied by the utility model,

$$switch_i^o = \delta + \beta_p switch_i^p + \varepsilon_i, \tag{6}$$

where ε_i is the error term. Similar to Section 5.1, the analysis is carried out for two sets of measures. The baseline analysis uses the combined preference measures, and the robustness analysis uses the measures obtained from the tasks with the lowest number of multiple switchers.

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

[12] The non-parametric preference measures are restricted to in the interval [0,1], such that using OLS regressions might be considered problematic. In a robustness check, I implement a logit transformation of the aversion to unknown payoffs before estimating the model. The results are qualitatively similar to those reported in Table 6.

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

[14] In the risk-only case the expected utility of the Lotto lottery is $0.5 \cdot u(10)$. 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 6
Analysis of aversion to unknown payoffs (non-parametric preference measures).

Panel A: Baseline specification — Correlation statistics			
	Aversion to unknown payoffs Combined measure	Risk aversion Combined measure	Ambiguity aversion Combined measure
Aversion to unknown payoffs		0.304***	0.281***
Combined measure		(0.003)	(0.006)
Risk aversion	0.372***		0.103
Combined measure	(0.000)		(0.327)
Ambiguity aversion	0.290***	0.097	
Combined measure	(0.005)	(0.356)	
Panel B: Robustness specification — Correlation statistics			
	Aversion to unknown payoffs Lotto task 2	Risk aversion Risk task 2	Ambiguity aversion Ambiguity Task 1
Aversion to unknown payoffs		0.571***	0.290***
Lotto task 2		(0.000)	(0.005)
Risk aversion	0.622***		0.276***
Risk task 2	(0.000)		(0.008)
Ambiguity aversion	0.313***	0.253**	
Ambiguity task 1	(0.002)	(0.014)	
Panel C: Baseline specification — OLS regressions			
	Aversion to unknown payoffs Combined measure		
Risk aversion $\hat{\beta}_r$	0.464***		0.433***
Combined measure	(0.000)		(0.000)
Ambiguity aversion $\hat{\beta}_a$		0.577***	0.511***
Combined measure		(0.005)	(0.008)
Constant $\hat{\delta}$	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 D: Robustness specification — OLS regressions			
	Aversion to unknown payoffs Lotto task 2		
Risk aversion $\hat{\beta}_r$	0.624***		0.582***
Risk task 2	(0.000)		(0.000)
Ambiguity aversion $\hat{\beta}_a$		0.551***	0.293**
Ambiguity task 1		(0.002)	(0.049)
Constant $\hat{\delta}$	0.167***	0.217**	0.035
	(0.001)	(0.024)	(0.667)
R^2	0.39	0.10	0.41
Observations	93	93	93

Taken together, these results show that both risk and ambiguity preferences are important to explain the subjects' attitude towards unknown payoffs. In direct comparison, the association with risk aversion is higher than the association with ambiguity aversion. To some extent, these results confirm that decision makers tend to behave as predicted by subjective expected utility theory, as conjectured by, e.g., Camerer and Weber (1992). Unknown payoffs 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) less uncertain payoff of roulette lotteries.

Yet, 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 payoffs in the Lotto lotteries, such it is natural to conceive that they do not form precise subjective probabilities for each of the potential prizes, but rather consider a range of probabilities possible. 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, i.e., the predicted switching points are consistently too low. This means that, given their risk and ambiguity preferences, subjects are predicted to switch earlier than they actually do – they are less averse to unknown payoffs than predicted. This pattern is also present in the descriptive statistics of the non-parametric preferences measures, see Section 4. While subjects are, on average, significantly risk and ambiguity averse, they are, on average, not averse to unknown payoffs.

6. Continuous range of payoffs

The tasks to measure aversion to unknown payoffs allow for only two different prizes, one of which is zero. This procedure might have two drawbacks. First, by offering only two possible values for the unknown payoff, subjects might be induced to think about the probability of each scenario, and thus have directly unknown probabilities in mind, rather than unknown payoffs. Second, the Lotto lotteries are 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.[15] Taken together, this might explain the explanatory power of ambiguity aversion for aversion to unknown payoffs.

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

Table 7
Predicting switching points.

Panel A: Baseline specification			
	Observed switching point (combined measure)		
Predicted switching point $\hat{\beta}_p$			
Risk aversion	0.330***		
(combined measure)	(0.003)		
Ambiguity aversion		0.399**	
(combined measure)		(0.023)	
Risk and ambiguity aversion			0.352***
(combined measure)			(0.000)
Constant $\hat{\delta}$	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: Robustness specification			
	Observed switching point (Lotto task 2)		
Predicted switching point $\hat{\beta}_p$			
Risk aversion	0.640***		
(risk task 2)	(0.000)		
Ambiguity aversion		0.551***	
(ambiguity task 2)		(0.002)	
Risk and ambiguity aversion			0.520***
(risk task 2, ambiguity task 1)			(0.000)
Constant $\hat{\delta}$	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 coefficient estimates of OLS regressions of the observed switching points in the Lotto tasks ($switch_i^o$) on the predicted switching point ($switch_i^p$),

$$switch_i^o = \delta + \beta_p switch_i^p + \varepsilon_i, \quad (6)$$

where ε_i is the error term. The predicted switching points are calculated using the risk (γ) and ambiguity (α) preference parameters obtained from the risk and ambiguity tasks, using the functional forms presented in Eqs. (4) and (5).
Panel A reports the results using the combined preference measures (the baseline specification). Panel B reports the results using the measures obtained from Lotto task 2, risk task 2, and ambiguity task 1 (the robustness specification). p-values are given in parenthesis below. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

While this behaviour is in line with the compound lottery model which treats unknown payoffs as a set of as known payoffs with unknown probabilities, the idea of Lotto lotteries goes beyond that; subjects not having any information about possible payoffs. The experimental literature in psychology, for example, does not restrict the payoffs to take on only a few possible values. Instead, these studies only specify a possible range for the payoffs, allowing for all potential payoffs within that range. When leaving the set of payoffs (almost completely) unspecified, subjects cannot jump into probability considerations for the unknown payoff. This section therefore introduces another experimental task designed to measure aversion to unknown payoffs when the prize of the Lotto lottery is continuous.

Yet, decision tasks allowing for a continuous range of payoffs come with several drawbacks. First, receiving a payoff from a continuous range cannot be transformed into draws of balls with different colours. As a consequence, it is more difficult to implement a mechanism that avoids subjects to form non-symmetric subjective probability distributions over the range of payoffs. Such a procedure would require subjects to allocate a different colour to each payoff, which is not possible for a continuous payoff. Without such a mechanism, decision makers might believe that the payoffs are rather low, e.g., to save on the experimenter's budget (see the discussion in Section 3.2).

Second, allowing for continuous ranges of payoffs might reduce size of the empirically observed aversion to unknown payoffs. To the extent risk preferences can explain the observed behaviour, a continuous payoff 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 aversion to unknown payoffs should be more pronounced.

Finally, continuous payoffs do not allow for an unambiguous mapping between risk aversion and aversion to unknown payoffs. 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 payoff range. In these session I use a new task to measure the subjects' aversion to unknown payoffs (*Lotto task 3*), which is a variant of Lotto task 2. Instead of offering an unknown payoff of either 0 or 10, subjects are offered an unknown payoff in the range from 0 to 10 (see Appendix B). The degenerate roulette lottery is identical to Lotto task 2. Similar to Lotto task 2, subjects 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 at some point. The earlier they switch, the more they are averse to unknown payoffs.

The second round of experiments also includes the tasks used in the robustness specification of the main analysis, i.e., Lotto 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.

The table summarizes the results of the second set of experiments. Panel A reports the non-parametric measures of aversion to unknown payoffs (Lotto tasks 2 and 3), risk, and ambiguity aversion. Lotto task 2 offers two possible payoffs (0 or 10 points) when selecting the option with unknown payoff; Lotto task 3 offers the a range of payoffs (from 0 to 10 points) when selecting the option with unknown payoff. Significance of the difference to 0.5 is estimated using a t-test. Panel B reports the correlation statistics between the two measures of aversion to unknown payoffs derived from Lotto tasks 2 and 3. The lower part of the panel presents the Pearson correlation, the upper part the Spearman correlation.

Panel C presents the coefficient estimates of OLS regressions of the non-parametric preference measure of aversion to unknown payoffs obtained from Lotto task 3 on risk and ambiguity preferences,

$$lotto_i = \delta + \beta_r risk_i + \beta_a amb_i + \varepsilon_i, \quad (3)$$

where $lotto_i$ denotes the non-parametric measure of aversion to unknown payoffs, $risk_i$ is the non-parametric measure of risk aversion, amb_i is the non-parametric measure of ambiguity aversion, and ε_i is the error term.

Panel D presents the coefficient estimates of OLS regressions of the observed switching points in the Lotto task 3 ($switch_i^o$) on the predicted switching point ($switch_i^p$),

$$switch_i^o = \delta + \beta_p switch_i^p + \varepsilon_i, \quad (6)$$

where ε_i is the error term. The predicted switching points are calculated using the risk (γ) and ambiguity (α) preference parameters obtained from the risk and ambiguity tasks, using the functional forms presented in Eqs. (4) and (5). 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 B and C.

Panel A of Table 8 shows that the replication of the three tasks used in the main analysis yields similar results in this second sample. As before, Lotto task 2 shows that subjects are slightly averse to unknown payoffs on average, but the value of 0.527 is not statistically different

Table 8
Continuous payoffs.

Panel A: Descriptive statistics of non-parametric preference measures

	Observations	Mean	Standard deviation	Lowest	Highest
Aversion to unknown payoffs					
Lotto task 2	100	0.527	0.164	0.05	0.95
Lotto task 3	100	0.522*	0.130	0.25	0.95
Risk aversion					
Risk task 2	100	0.560***	0.151	0.25	0.95
Ambiguity aversion					
Ambiguity task 1	100	0.541***	0.124	0.15	0.95

Panel B: Correlation statistics (Aversion to unknown payoffs)

	Lotto task 2	Lotto task 3
Lotto task 2		0.528***
Lotto task 3	0.608***	

Panel C: Aversion to unknown payoffs

	Aversion to unknown payoffs (Lotto task 3)		
Risk aversion $\hat{\beta}_r$	0.500***		0.425***
(risk task 2)	(0.000)		(0.000)
Ambiguity aversion $\hat{\beta}_a$		0.457***	0.313***
(ambiguity task 1)		(0.000)	(0.000)
Constant $\hat{\delta}$	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: Predicting switching points

	Observed switching point (Lotto task 3)		
Predicted switching point $\hat{\beta}_p$			
Risk aversion	1.099***		
(risk task 2)	(0.000)		
Ambiguity aversion		0.456***	
(ambiguity task 2)		(0.000)	
Risk and ambiguity aversion			0.383***
(risk task 2, ambiguity task 1)			(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

from 0.5. The risk and ambiguity measures indicate, as before, that subjects are risk and ambiguity averse.

The new Lotto task 3 confirms that subjects are averse to unknown payoffs. Different from Lotto task 2, the 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 both measures are highly correlated, reaching a linear correlation of 61%. A paired t-test confirms that both measures are not statistically different from each other. These results show that subjects treat a range of payoffs from 0 to 10 similar to the binary case with a payoff that can be either 0 or 10. It seems that the absence of a mechanism to induce symmetric beliefs about the prize in the Lotto lottery does lead to an increasing aversion to unknown payoffs.

Panel C repeats the analysis of non-parametric preference measures when allowing the unknown payoff to lie in a range from 0 to 10. The results are similar to those of the main analysis. Both risk and ambiguity preferences are strongly related to the subjects' aversion to unknown payoffs, with both coefficients being highly significant.

Finally, panel D replicates the comparison between observed and predicted switching points. 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 over the range of payoffs from 0 to 10. Since a uniform distribution over all possible payoffs reduces the variance of expected payoffs, the explained variance of predicted switching points for actual switching points is lower in the risk-only case 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 end-points 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, this section shows that replacing the binary payoff space of a Lotto lottery with a continuous payoff range does not change the results. By and large, subjects deal with both types of unknown payoff structures in a similar way. Even though the compound lottery model expresses unknown payoffs as a countable set of known payoffs, it seems to be capturing the behaviour of a continuous payoff space as well. A possible explanation for this behaviour is that subjects (unconsciously) reduce continuous payoffs to a binary payoff space, and then decide in accordance with their risk and ambiguity preferences — as before. This result mirrors earlier empirical evidence suggesting that the $\alpha-$MEU model by Ghiradato et al. (2004) is a suitable model for choice tasks under ambiguity (Ahn et al., 2014).

An important implication of these findings is that the results are valid for the general case of entirely unknown payoffs. This, in turn, means that the findings can be compared to the results in the psychology and management science literature which usually assume a range of unknown payoffs in their experiments.

7. Concluding remarks

Analysing decision making under uncertainty when payoffs are inherently unknown, like the Lotto lotteries studied in this paper, has not been at the centre of research in economics. 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.

This paper suggests thinking about unknown payoffs 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 a subjects' aversion to unknown payoffs, as conjectured by Camerer and Weber (1992). However, if these subjective probabilities are not singleton (but rather consist of a set of probabilities), ambiguity aversion has also a role in explaining aversion to unknown payoffs. The empirical finding that both risk and ambiguity preferences matter provides evidence for the latter. This means that unknown payoffs are ultimately closely linked to ambiguity about probabilities.

These findings have some important implications. Given that many decisions in our daily lives involve unknown payoffs, 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 unknown 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 unknown payoffs and ambiguity about probabilities. The results of this paper thus confirm these models empirically.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Numerical examples for preference of roulette lotteries over Lotto lotteries

This appendix provides some numerical examples for the conjectured preference of roulette lotteries (urn H) over Lotto lotteries (urn F), as discussed in Section 2.3.1, caused by (1) risk aversion and (2) ambiguity aversion.

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

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

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

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

Note that the MEU-model by Gilboa and Schmeidler (1989) is a special case where $\alpha = 1$, and thus results in the same choice pattern.

Aversion to Lotto lotteries relative to roulette lotteries can also be rationalized by non-symmetric subjective probability distributions or non-symmetric ranges of ambiguity. In this case the choice is independent from risk or ambiguity preferences. The experimental set-up used in this study thus ensures symmetric beliefs.

Appendix B. Incentivized decision tasks

This appendix presents the incentivized decision tasks to measure risk and ambiguity preferences, as well as aversion to unknown payoffs. 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. Screenshots of the experimental tasks are presented in the online appendix.

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.*

Table B.1
Risk task 1.

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

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 do not 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?

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 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)?

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 do not 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.[16]

- *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.*

[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 white. If the selected colour is black, the word "white" has to be replaced by "black", and vice versa.

Table B.2
Risk task 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

Table B.3
Ambiguity task 1.

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

- *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.[17]

In each situation, from which box do you prefer to draw a ball, box 1 or 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 do not 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.[18]

- *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 do not 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

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

[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 white. If the selected colour is black, the word "white" has to be replaced by "black", and vice versa.

Table B.4
Ambiguity task 2.

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 11 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 16 black balls	20 white balls OR 20 black balls	Box X ○ ○ Box Y
14	2 white balls and 18 black balls	20 white balls OR 20 black balls	Box X ○ ○ Box Y

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.[19]

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

Lotto task 1: This task determines aversion to unknown payoffs 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 do not 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[20]:

- *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 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 will randomly draw one ball from the box. If the colour of that ball is yellow you earn 10 points, and nothing otherwise.[21]

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

Lotto task 2: This task determines aversion to unknown payoffs 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[22]:

- *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.*

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

[20] 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.

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

[22] 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.

Table B.5
Lotto task 1.

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

Table B.6
Lotto task 2.

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

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 will randomly draw one ball from the box. If the colour of that ball is yellow you earn 10 points, and nothing otherwise.[23]

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)?

Lotto task 3: This task determines aversion to unknown payoffs by eliciting a certainty equivalent of a continuous ambiguous lottery.[24]

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)?

Appendix C. Non-parametric preference measures

This appendix describes how the switching points in the binary choice tasks are transformed into the non-parametric measures of aversion to unknown payoffs, risk aversion and ambiguity aversion as presented in Section 4.

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 measures by linearly mapping the indifference point into an interval between 0 and 1. A value of 0 corresponds to extreme liking of unknown payoffs (risk/ambiguity seeking preferences), while a number of 1 means extreme aversion to unknown payoff (risk/ambiguity aversion). A value of 0.5 implies neutrality.

Lotto tasks: Under the assumption of risk and ambiguity neutrality, a subject is indifferent in situation 5 (for all Lotto tasks) since the expected value of both options are identical.

To see this, consider Lotto task 1, situation 5. The expected value of the risky option (box I) is $0.5 \cdot 5 + 0.5 \cdot 0 = 2.5$. In the Lotto lottery (box J), the expected value is $0.5(10\mu^Y + 0\mu^B)5 + 0.5 \cdot 0 = 5\mu^Y$, where μ^Y denotes the subjective probability for the coloured ball to be yellow, and μ^B the subjective probability for the coloured ball to be blue. Since prior to Lotto task 1, subjects are asked to select the colour that provides points, subjects do not have any incentive to attribute unequal (asymmetric) beliefs about the two scenarios, which implies symmetric beliefs $\mu^Y = \mu^B = 0.5$. Hence, the expected value of the Lotto lottery is equally 0.5. Indifference at situation 5 hence corresponds to a neutral attitude with respect to lotteries with unknown payoffs.

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

[24] This task was only used in the second round of experiments, see Section 6. These sessions consisted of risk task 2, ambiguity task 1, Lotto task 1, and Lotto task 3 only.

Table B.7
Lotto task 3.

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

For Lotto tasks 2 and 3, if a subject prefers in situation 0 a certain payoff of 0 points over an unknown payoff which can be at worst 0 points, this corresponds to extreme aversion to unknown payoffs and is assigned a measure of 1. If a subject prefers in situation 10 an unknown payoff which can be at best 10 points over a certain payoff of 10 points, this corresponds to extreme liking of unknown payoffs and is assigned a measure of 0. Lotto task 1 follows the same logic. For all other switching points the measure is obtained by linear interpolation, using the mid-point around the switching point:

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

For example, a switch between situations 5 and 6 implies a preference measure of 0.45 (in all 3 Lotto 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.

Table D.1
Number of switching points per subject.

Number of switches	Subjects	Percent
6	63	67.74
8	11	11.83
10	4	4.30
12	8	8.60
14	0	0.00
16	2	2.15
18	3	3.23
20	1	1.08
22	1	1.08
Mean	7.85	

The table presents the number of switches of subjects in all 6 binary choice tasks combined (in the main experimental sessions).

Appendix D. Subjects with multiple switching points

This appendix presents additional analyses of subjects with multiple switching points in the binary choice lists, and explores whether the results of the study change if these subjects are removed from the sample. Appendix D.1 presents the descriptive statistics of the number of switching points for all subjects. Appendix D.2, as robustness check, shows that the main results do not change when excluding subjects that switch more than once.

D.1. Analysis of subjects with multiple switching points

The standard pattern in binary choice lists is to prefer one option over the other up to a switching point, from which the other option is the preferred choice (threshold strategy). Yet, it is common to observe that some subjects exhibit multiple switching points (Holt & Laury, 2002), a behaviour that is difficult to reconcile with rational choice. Despite being exposed to control questions before each choice task, multiple switching points might indicate a lack of understanding of the tasks, resulting in measurement errors.

Table D.1 presents the number of switches per subject in all 6 tasks combined (in the main experimental sessions). The table shows that 63 subjects (68% of the sample) switch once per task, and can thus be considered rational decision makers. Another 12% of subjects switch back and forth in one task, and thus have 8 total switches. The remaining 19 subjects switch more often.

D.2. Results for rational subjects

In the paper, subjects with multiple switching points are not excluded from the analysis. Instead, the study follows Falk et al. (2023) and defines a subject's switching point as the average switching point of all switching points. An alternative is to exclude subjects with multiple switching points from the sample, and carry out the analysis for the 63 rational subjects that have only one switching point per task.

Table D.2
Rational subjects.

Panel A: Descriptive statistics of non-parametric preference measures

	Observations	Mean	Standard deviation	Lowest	Highest
Aversion to unknown payoffs					
Lotto task 1	63	0.540*	0.167	0.05	0.95
Lotto task 2	63	0.507	0.147	0.15	0.95
Combined measure	63	0.524	0.129	0.20	0.90
Risk aversion					
Risk task 1	63	0.539**	0.135	0.25	0.95
Risk task 2	63	0.529	0.154	0.05	0.95
Combined measure	63	0.534**	0.103	0.25	0.95
Ambiguity aversion					
Ambiguity task 1	63	0.534***	0.083	0.25	0.65
Ambiguity task 2	63	0.535***	0.075	0.33	0.78
Combined measure	63	0.534***	0.059	0.36	0.66

Panel B: Correlation statistics

	Aversion to unknown payoffs			Risk aversion			Ambiguity aversion		
	Lotto task 1	Lotto task 2	Combined measure	Risk task 1	Risk task 2	Combined measure	Ambiguity task 1	Ambiguity task 2	Combined measure
Aversion to unknown payoffs									
Lotto task 1		0.459***	0.848***	0.022	0.356***	0.174	0.219*	0.077	0.195
Lotto task 2	0.345***		0.835***	0.077	0.588***	0.453***	0.294**	0.176	0.362***
Combined measure	0.845***	0.793***		0.019	0.556***	0.330***	0.313**	0.146	0.333***
Risk aversion									
Risk task 1	0.067	0.123	0.113		−0.151	0.648***	−0.111	0.021	−0.115
Risk task 2	0.283**	0.625***	0.539***	0.024		0.549***	0.301**	0.028	0.331***
Combined measure	0.254**	0.545***	0.475***	0.669***	0.759***		0.147	−0.012	0.136
Ambiguity aversion									
Ambiguity task 1	0.234*	0.302**	0.324***	−0.031	0.262**	0.175		0.115	0.756***
Ambiguity task 2	0.052	0.177	0.135	−0.061	0.039	−0.011	0.116		0.675***
Combined measure	0.197	0.324***	0.313**	−0.060	0.209	0.116	0.775***	0.718***	

Panel C: Analysis of aversion to unknown payoffs (non-parametric preference measures)

	Aversion to unknown payoffs			Aversion to unknown payoffs		
	Baseline specification			Robustness specification		
Risk aversion $\hat{\beta}_r$	0.592***		0.555***	0.597***		0.560***
	(0.000)		(0.000)	(0.000)		(0.000)
Ambiguity aversion $\hat{\beta}_a$		0.683**	0.571**		0.536**	0.263
		(0.013)	(0.020)		(0.016)	(0.154)
Constant $\hat{\delta}$	0.208***	0.159	−0.077	0.191***	0.221*	0.070
	(0.000)	(0.270)	(0.583)	(0.001)	(0.064)	(0.478)
R^2	0.23	0.10	0.29	0.39	0.09	0.41

Panel D: Predicting switching points

	Observed switching point			Observed switching point		
	Baseline specification			Robustness specification		
Predicted switching point $\hat{\beta}_p$						
Risk aversion	0.446***			0.597***		
	(0.001)			(0.000)		
Ambiguity aversion		0.537**			0.536**	
		(0.023)			(0.016)	
Risk and ambiguity aversion			0.408***			0.520***
			(0.000)			(0.000)
Constant $\hat{\delta}$	3.324***	3.020***	3.656***	2.964***	3.201***	3.332***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)	(0.000)
R^2	0.17	0.08	0.19	0.39	0.09	0.42

Table D.2 repeats the main analyses of this study for the subset of rational subjects. The results are very similar to those obtained from the entire sample of 93 subjects.

The table summarizes the results obtained from the sub-sample of rational subjects, i.e., subjects with only one switching point in each of the 6 tasks. Panel A reports the non-parametric preference measures derived from the switching points. Significance of the difference from 0.5 is estimated using a t-test. Panel B reports the correlation statistics between the non-parametric preference measures. The lower part of the panel presents the Pearson correlation, the upper part the Spearman correlation.

Panel C presents the coefficient estimates of OLS regressions of the non-parametric preference measures of aversion to unknown payoffs on risk and ambiguity preferences,

$$lotto_i = \delta + \beta_r risk_i + \beta_a amb_i + \varepsilon_i, \quad (3)$$

where $lotto_i$ denotes the non-parametric measure of aversion to unknown payoffs, $risk_i$ is the non-parametric measure of risk aversion, amb_i is the non-parametric measure of ambiguity aversion, and ε_i is the error term.

Panel D presents the coefficient estimates of OLS regressions of the observed switching points ($switch_i^o$) on the predicted switching point ($switch_i^p$),

$$switch_i^o = \delta + \beta_p switch_i^p + \varepsilon_i, \quad (6)$$

where ε_i is the error term. The predicted switching points are calculated using the risk (γ) and ambiguity (α) preference parameters obtained from the risk and ambiguity tasks, using the functional forms presented in Eqs. (4) and (5). 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 B and C.

Appendix E. Supplementary data

The screenshots of the experimental tasks can be found online at https://doi.org/10.1016/j.socec.2024.102310.

Data availability

Data will be made available on request.

References

Ahn, David, Choi, Syngjoo, Gale, Douglas, & Kariv, Shachar (2014). Estimating ambiguity aversion in a portfolio choice experiment. *Quantitative Economics*, *5*(2), 195–223.

Andersen, Steffen, Harrison, Glenn W., Lau, Morten I., & Rutström, E. Elisabet (2008). Eliciting risk and time preferences. *Econometrica*, *76*(3), 583–618.

Anscombe, F., & Aumann, R. (1963). A definition of subjective probability. *The Annals of Mathematical Statistics*, *34*, 199–205.

Bade, Sophie (2015). Randomization devices and the elicitation of ambiguity-averse preferences. *Journal of Economic Theory*, *159*, 221–235.

Budescu, David V., Kuhn, Kristine M., Kramer, Karen M., & Johnson, Timothy R. (2002). Modeling certainty equivalents for imprecise gambles. *Organizational Behaviour and Human Decision Processes*, *88*, 748–768.

Budescu, David V., & Templin, Sara (2008). *Decision making and behavior in complex und uncertain environments* (pp. 253–275). New York: Springer, chapter Valuation of Vague Prospects with Mixed Outcomes.

Butler, Jeffrey V., Guiso, Luigi, & Jappelli, Tullio (2014). The role of intuition and reasoning in driving aversion to risk and ambiguity. *Theory and Decision*, *77*, 455–484.

Camerer, Colin, & Weber, Martin (1992). Recent developments in modeling preferences. *Journal of Risk and Uncertainty*, *5*(4), 325–370.

Cavatorta, Elisa, & Schröder, David (2019). Measuring ambiguity preferences: A new ambiguity preference survey module. *Journal of Risk and Uncertainty*, *58*, 71–100.

Chakravarty, Sujoy, & Roy, Jaideep (2009). Recursive expected utility and the separation of attitudes towards risk and ambiguity: an experimental study. *Theory and Decision*, *66*(3), 199–228.

Charness, Gary, Karni, Edi, & Levin, Dan (2013). Ambiguity attitudes and social interactions. *Journal of Risk and Uncertainty*, *46*, 1–25.

Chow, Clare Chua, & Sarin, Rakesh K. (2002). Known, unknown, and unknowable uncertainties. *Theory and Decision*, *52*, 127–138.

Dempster, A. P. (1967). Upper and lower probabilities induced by a multivalued mapping. *The Annals of Mathematical Statistics*, *38*, 325–339.

Denoeux, Thierry (2019). Decison-making with belief functions: A review. *International Journal of Approximate Reasoning*, *109*, 87–110.

Dimmock, Stephen G., Kouwenberg, Roy, Mitchell, Olivia S., & Peijnenburg, Kim (2015). Estimating ambiguity preferences and perceptions in multiple prior models: Evidence from the field. *Journal of Risk and Uncertainty*, *51*(3), 219–244.

Dimmock, Stephen G., Kouwenberg, Roy, Mitchell, Olivia S., & Peijnenburg, Kim (2016). Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics*, *119*(3), 559–577.

Du, Ning, & Budescu, David V. (2005). The effects of imprecise probabilities and outcomes in evaluating investment options. *Management Science*, *51*(12), 1791–1803.

Eliaz, Kfir, & Ortoleva, Pietro (2016). Multidimensional ellsberg. *Management Science*, *62*(8), 2179–2197.

Ellsberg, D. (1961). Risk, ambiguity and the savage axioms. *Quarterly Journal of Economics*, *75*(4), 643–669.

Falk, Armin, Becker, Anke, Dohmen, Thomas, Huffman, David, & Sunde, Uwe (2023). The preference survey module: A validated instrument for measuring risk, time and social preferences. *Management Science*, *69*(4), 1935–1950.

Fischbacher, Urs (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, *10*(2), 171–178.

Friedman, Daniel, Habib, Sameh, James, Duncan, & Williams, Brett (2022). Varieties of risk preference elicitation. *Games and Economic Behavior*, *133*, 58–76.

Ghiradato, Paolo (2001). Coping with ignorance: unforseen contingencies and non-additive uncertainty. *Economic Theory*, *17*, 247–276.

Ghiradato, Paolo, Maccheroni, Fabio, & Marinacci, Massimo (2004). Differentiating ambiguity and ambiguity attitude. *Journal of Economic Theory*, *118*, 133–173.

Gilboa, Itzhak (1987). Expected utility with purely subjective non-additive probabilities. *Journal of Mathematical Economics*, *16*, 65–88.

Gilboa, Itzhak, & Schmeidler, David (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics*, *18*, 141–153.

Gonzáles-Vallejo, Claudia, Bonazzi, Alberto, & Shapiro, Andrea J. (1996). Effect of vague probabilties and of vague payoffs on preference: A model comparison analysis. *Journal of Mathematical Psychology*, *40*, 130–140.

Ho, Joanna L. Y., Keller, L. Robin, & Keltyka, Pamela (2001). Managers' variance investigation decisions: An experimental examination of probabilistic and outcome ambiguity. *Journal of Bahavioral Decision Making*, *14*(4), 257–278.

Ho, Joanna L. Y., Keller, L. Robin, & Keltyka, Pamela (2002). Effects of outcome and probalistic ambiguity on managerial choices. *Journal of Risk and Uncertainty*, *24*(1), 47–74.

Holt, Charles A., & Laury, Susan K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655.

Hurwicz, L. (1951). Optimality criteria for decision making under ignorance. Cowles Communication Discussion Paper, Statistics No. 370.

Jaffray, Jean-Yves (1989). Linear utility theory for belief functions. *Operations Reseach Letters*, *8*, 107–112.

Kuhn, Kristine M., & Budescu, David V. (1996). The relative importance of probabilties, outcomes, and vagueness in hazard risk decisions. *Organizational Behaviour and Human Decision Processes*, *68*(3), 301–317.

Kuhn, Kristine M., Budescu, David V., Hershey, James R., Kramer, Karan M., & Rantilla, Adrian K. (1999). Attribute tradeoffs in low probability/high consequence risks: the joint effects of dimension preference and vagueness. *Risk Decision and Policy*, *4*(1), 31–46.

Lauriola, Marco, & Levin, Irwin P. (2001). Relating individual differences in attitude toward ambiguity to risky choices. *Journal of Behavioral Decision Making*, *14*(2), 107–122.

Mukerji, Sujoy (1997). Understanding the nonadditive probability model. *Economic Theory*, *9*, 23–46.

von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behaviour*. Princeton, NJ: Princeton University Press.

Onay, Selcu, La-Ornual, Dolchai, & Öncüler, Ayse (2013). The effect of temporal distance on attitudes toward imprecise probability and imprecise outcomes. *Journal of Behavioural Decision Making*, *26*, 362–374.

Parez, Fabian, Hollard, Guillaume, & Vranceanu, Radu (2021). How serious is the measurement-error problem in risk-aversion tasks?. *Journal of Risk and Uncertainty*, *63*, 319–342.

Savage, Leonard J. (1954). *The foundations of statistics*. New York: Wiley.

Schmeidler, David (1989). Subjective probability and expected utility without additivity. *Econometrica*, *57*(3), 571–587.

Schoemaker Paul, J. H. (1989). Preferences for information on probabilities versus prizes: The role of risk-taking attitudes. *Journal of Risk and Uncertainty*, *2*, 37–60.

Shafer, G. (1976). *A mathematical theory of evidence*. Princeton, NJ: Princeton University Press.

Spearman, C. (1904). The proof and measurement of association between two things. *American Journal of Psychology*, *15*, 72–101.

Vieider, Ferdinand M. (2018). Certainty preference, random choice, and loss aversion: A comment on violence and risk preference: Experimental evidence from Afghanistan. *American Economic Review*, *108*(8), 2366–2382.

Viero, Marie-Louise (2009). Exactly what happens after the anscombe-aumann race?. *Economic Theory*, *41*(2), 175–212.

Wang, Xinghua, & Navarro-Martinez, Daniel (2023). Increasing the external validity of social preference games by reducing measurement error. *Games and Economic Behaviour*, *141*, 261–285.