Preferences over timing of uncertainty under risk and ambiguity: an experiment

Julen Zarate-Pina*

7 November, 2022

Abstract

This paper empirically analyses two types of preferences over the timing of resolution of uncertainty: preferences between early and late resolution and preferences between one-shot and gradual resolution of lotteries under risk and ambiguity. In an on-line experiment with students, we find significant differences between treatments: under risk, a majority of participants show a strict preference against gradual resolution of uncertainty, for low, medium and high ex-ante probabilities of receiving the prize of the lottery. Under ambiguity, most participants show a preference for gradual resolution of uncertainty for lotteries with a low-likelihood of winning, and an aversion towards it for medium and high likelihoods. Additionally, in both treatments we find subjects show strict preferences more frequently in the one-shot vs. gradual resolution dimension than in the early vs. late resolution dimension. Results from the experiment contribute to the literature about the empirical validity of ambiguity models, as different models prescribe different preferences over the timing of the resolution of uncertainty.

Acknowledgements

Financial support from Fundación Ramón Areces is gratefully acknowledged. I would also like to thank Antonio Cabrales, Terri Kneeland, Ryan Kendall, Kirby Nielsen, Martin Cripps and participants at ESA 2022 Online Meeting, red3c and EHU-UPV seminar participants for valuable comments.

*University College London, Department of Economics, julen.pina@ucl.ac.uk

1 Introduction

Under expected utility theory, receiving interim information about the outcome of a decision after it has been made (namely, non-instrumental information) should always be weakly preferred to not receiving it, as decision-makers are assumed to account for any further information they may receive in the future when making the decision (in other words, they satisfy the reduction of compound lotteries axiom). Additionally, standard theory also assumes that the time in which they learn the outcome of a decision should not matter when making the decision either (i.e. they satisfy the time neutrality axiom, as defined by Segal, 1990).

In this work, we study the empirical validity of these axioms in an ambiguous setting, that is, in a setting in which the exact probability of states of the world is unknown. We do this by designing and implementing an experiment in which we compare preferences related to the axioms (and their deviations) between subjects assigned to making decisions in an environment in which probabilities are known, and one in which they are not. Additionally, we study the theoretical implications of deviations from the axioms on the empirical validity of several ambiguity models.

Deviations from the above mentioned axioms can have significant economic implications. For instance, subjects in a laboratory experiment have been shown to be more risk averse when they receive more frequent feedback about their performance, therefore, leading them to reach suboptimal levels of stock investments (Gneezy and Potters, 1997), even after controlling for the possibility of dynamic investment (Bellemare, 2005). Kocher et al. (2014) also showed, in an experimental setting, that feelings of hope and anticipation incentivised participants to take part in the national lottery in the Netherlands, and to delay as much as possible the resolution of that lottery.

Beyond this laboratory evidence, learning about preferences over non-instrumental information can also help to isolate the non-pecuniary cost of this information from the total effect of instrumental information. One frequent example of such information mechanisms are genetic tests of diseases, which are becoming ever more commonplace. These tests provide information about genetic mutations that have been found to be correlated with an increased chance of developing certain diseases (Evans et al., 2001). Some of these diseases (such as multiple endocrine neoplasia type 2) are almost always preventable if the associated mutations are detected. The probability of suffering other diseases can also be expected to increase given certain mutations, but no effective treatment exists to prevent their development (for instance, Alzheimer's disease), and other diseases lie somewhere in between (e.g. breast and ovarian cancer). This last example is paradigmatic of the interrelation between the instrumental and non-instrumental value of information[1]. The results of such a test are partly instrumental as they can incentivise surgical interventions to reduce the risk of developing this disease; however, this information can also be non-instrumental as successful prevention of the disease is not guaranteed, and as a result, learning about the increased risk can create negative anticipatory feelings due to the increased risk of developing the disease. In these cases understanding preferences over non-instrumental information is essential to perform a welfare analysis of the value of these tests to individuals.

There is an increasing experimental literature on preferences over non-instrumental information (Ahlbrecht and Weber, 1997; Lovallo and Kahneman, 2000; Budescu and Fischer, 2001; Zimmermann, 2015; Masatlioglu et al., 2017; Nielsen, 2020). All of these papers have focused on cases in which the ex-ante and interim probabilities of outcomes are perfectly known or *risky*. In real life, however, learning the exact probabilities of outcomes is in many cases impossible. Following on the example of genetic tests above, there exist competing studies that report different probabilities of developing a disease given a mutation (Chen and Parmigiani, 2007), and idiosyncratic variables, such as lifestyle and additional mutations, can increase the uncertainty about the real probability of suffering the disease. The same can be said about other phenomena that have deep and widespread economic and social effects, such as the recent Covid-19 pandemic or climate change. The limited, evolving and often conflicting understanding of these events generates ambiguity about the future state.

In a recent policy paper, Berger et al. (2020) discuss the three sources of uncertainty that an imperfect understanding of a crisis like the pandemic are related to: uncertainty within models, across models and about models. The first type of uncertainty is the one that is considered in risky problems. For instance, quantitative models make assumptions about random shocks with known distributions that lead to estimates of the probability of an event occurring. Uncertainty across models (e.g. conflicting evidence) and about models (for instance, missing variables, incorrect specification of models) are instead related to unmeasurable uncertainty or ambiguity. Receiving more information from new studies may increase this unmeasurable uncertainty[2].

Given the ubiquity of non-neutral attitudes towards ambiguity (Trautmann and de Kuilen, 2015), it is important to understand how the availability of uncertain or ambiguous information affects decision-making in these situations, and other decision-making processes. In this paper, we perform an experimental analysis in which we study the two types of preferences over non-instrumental information mentioned above: preferences over early or late resolution of un-

[1]Lerman et al. (1996) offered a free test of genetic mutations to a sample of men and women with a family history of genetically determined breast-ovarian cancer. Only 43% of the participants in the study asked to learn the results of the test.

[2]For instance, in a meta-analysis of 172 observational studies Chu et al. (2020) find that the reduction in the risk of being infected by the SARS-CoV-2 virus by using a mask ranges from 6% to 80%, depending on the study.

certainty, and preferences over one-shot or gradual resolution of uncertainty. We construct two between-subject treatments: risk and ambiguity. In the risk treatment, participants are shown lotteries in which ex-ante and interim probabilities (when further information is provided) of winning the prize are known; in the ambiguity treatment, on the other hand, the exact ex-ante and interim probabilities of winning the lottery are unknown. Within each treatment subjects have to make 20 pairwise choices. These pairwise choices are composed of two lotteries that may differ in two aspects: they can be lotteries that are resolved in one stage (one-shot lotteries), or lotteries resolved over two periods (gradually resolved lotteries); if they are one-shot lotteries, they can also be resolved either early or late. Comparisons along the former aspect allow to study if subjects have preferences about learning partial non-instrumental information before the lottery is resolved, or instead show aversion towards learning this partial information. Comparisons along the latter aspect can show preferences over early or late resolution of uncertainty. The lotteries we compare, on the other hand, both have the same ex-ante probability of winning so they only differ in how the information is learnt. Gradually resolved lotteries share the same variance as well, so none are more informative than others.

We consider two additional within-subject treatments: across pairwise choices we vary the ex-ante likelihood or probability of winning the lottery. We do this to test whether different likelihoods of the good outcome occurring affect preferences, especially in the ambiguity treatment, as it has already been established that the likelihood of an event occurring can lead to changing attitudes towards ambiguity (Dimmock et al., 2013, 2016, Bouchouicha et al., 2017). In the risk treatment we also consider positively and negatively skewed lotteries. Masatlioglu et al., 2017 show that i) more participants have a preference to resolve the lottery early than late as the probability of winning the prize goes up, ii) preference for positively skewed lotteries over negatively skewed lotteries is greater for higher probability of the desired outcome. We include this additional within-subject treatment to test preferences between one-shot and gradually resolved (positively and negatively skewed) lotteries at different probabilities of winning the lottery.

Finally, following the theoretical work linking ambiguity models and preferences over the timing of resolution of uncertainty (Strzalecki, 2013, Li, 2020), we also reach conclusions about the empirical validity of several ambiguity models (maxmin model, multiplier model, Choquet utility model).

Our results show that there exist significant differences in preferences over gradual resolution of uncertainty between risk and ambiguity treatments. Under risk, we find no significant effect of the ex-ante likelihood of the lottery affecting these preferences. Under ambiguity, however, there is a shift from a majority of participants liking gradual resolution at low likelihoods of winning the lottery, to most of them becoming averse to it for higher levels of likelihood. This attitude is orthogonal to attitudes towards ambiguity, and as a result, none of the models we study can explain this behaviour. It can, however, help develop new ambiguity models that can better explain this empirical evidence.

Related literature

Our work is most closely related to three strands of the literature: empirical papers on preferences over the timing of resolution under risk, experimental analysis of ambiguity models, and a recent strand of the literature on ambiguous signals.

Ahlbrecht and Weber (1997), and Lovallo and Kahneman (2000) first studied how anticipation about the outcome of a hypothetical lottery, and the implications of its structure (specifically its skewness and whether it reports gains or losses) affect preferences over one-shot or gradual resolution of uncertainty, between positively and negatively skewed lotteries and with different ex-ante probabilities of winning. In incentivised experiments, Abdellaoui et al. (2010) showed that subjects become more risk loving as the outcome of a lottery is delayed and Kocher et al. (2014) that a large minority of participants in an experiment had a strict preference to receive a ticket to a real state-run lottery whose draw is performed later rather an early. With respect to learning partial information, Eliaz and Schotter (2010) find that in risky choices, participants in an experiment choose to pay for non-instrumental information. They relate this to the 'confidence effect', that is, participants want to become more confident that they made the right decision by acquiring this additional information. Zimmermann (2015), on the other hand, observed that approximately half of the participants in his experiment preferred to receive information in one period, whilst the other half had a preference for gradual resolution of uncertainty throughout a whole week. Falk and Zimmermann (2016) considered a decision in the domain of losses and concluded that if a distracting activity is available before learning the outcome, subjects show a preference to delay learning about the outcome. Masatlioglu et al. (2017) find that subjects usually have a preference for positively skewed risky lotteries, or lotteries that are more informative in the good state, than negatively skewed lotteries, and this preference becomes stronger the higher is the ex-ante probability of winning the lottery. Finally, most recently, Nielsen (2020) studied differences in preferences in the timing of the resolution of uncertainty if the outcome of the lottery has already been resolved and if it is still has to be resolved. She found, using an interesting experimental approach where no constraints were set on the choice of lotteries, that in the former case there is a preference for early resolution of uncertainty and in the latter case there is a preference for later resolution of uncertainty.

These empirical papers stem from theoretical work pioneered by Kreps and Porteus (1978). They first considered the issue of non-indifference towards the timing of information axiomatically. Their work was further refined by Grant et al. (1998, 2000). Dillenberger (2010) linked a preference for one-shot resolution of uncertainty to the certainty effect, as shown by the Allais paradox (1953). Palacios-Huerta (1999) provided a first behavioural foundation to the aversion to partial information by linking it to disappointment aversion, as described by Gul (1991). Koszegi and Rabin (2009) similarly explain that partial information will be avoided by assuming loss aversion in a consumption model with an endogenous reference point. Hoy et al. (2015) show that ambiguity aversion (characterised as a 'dilation' of priors[3]) could explain the low take-up rate of genetic tests. Ely et al. (2015) go against the previous papers and propose that suspense (modelled as shifts in the prior about the outcome of an event) can actually lead to a preference for partial information.

Our work also relates to the growing literature on empirical tests of ambiguity models. Halevy (2007) analysed the validity of subjective expected utility, maxmin and the smooth model, by analysing preferences over compound lotteries and ambiguous lotteries. Conte and Hey (2013) estimated parametric versions of the subjective expected utility model, the smooth model, the rank dependent expected utility and the α-maxmin model. Baillon et al. (2015) concluded that prospect theory best explains ambiguity attitudes, in an experiment with positive and negative ambiguous lotteries[4]. As far we are aware, ours is the first paper to check the empirical validity of ambiguity models by studying preferences over the timing of the resolution of ambiguous lotteries.

Lastly, there exists a recent branch of the ambiguity literature that studies attitudes towards ambiguous information. Epstein and Halevy (2020) experimentally test the martingale property of Bayesian updating in an environment in which the likelihood of the outcome of a lottery is ambiguous and subjects also have ambiguity about the extent of the informativeness of the signal, by eliciting conditional and unconditional probability equivalents of the lotteries. Liang (2021) considers an experiment where the prior about the outcome of a lottery is risky and the informativeness (whether the signal is true or misleading) is uncertain, or vice versa. It also elicits certainty equivalents of conditional and unconditional lotteries. Kellner et al. (2020) look at how ambiguous information leads to changes in beliefs about the state of the world[5]. The approach of these three papers is very different to ours, as they do not study the aversion to

[3]Dilation of priors is defined as the extension of the set of possible priors after receiving a signal (Seidenfeld, Wasserman, 1993).

[4]Other papers that evaluate ambiguity models are Andersen et al. (2009), Hayashi and Wada (2010), Abdellaoui et al. (2011), Ahn et al. (2014), Hey et al. (2014), Chew et al. (2017), Cubitt et al. (2020).

[5]De Filippis et al. (2021) also study belief updating under ambiguity in a social environment.

gradual resolution of uncertainty. The first two papers elicit conditional certainty or probability equivalents, thus, already doing away with the aversive nature that may be related to receiving the partial information, and in which we are most interested. In Kellner et al. (2020) subjects always receive partial information, so the authors do not study the possibility of aversion towards gradual resolution of uncertainty either. Shishkin and Ortoleva (2021) is the paper closest to ours in its motivation. They study the value of information in an experiment in which they allow for "dilation" of priors, which is a common feature of models like maxmin and the smooth models, under certain conditions. They consider risky and ambiguous priors over the outcome of the lottery and ambiguous information about the trustworthiness of the signal. Their experiment differs from ours in three key aspects: i) we compare risky lotteries with risky information to ambiguous lotteries with ambiguous information; ii) in the ambiguity treatment of our experiment, we consider the case in which the prior is ambiguous and the partial information (or signal) that is received enforces a dilation of the priors. This allows to pin down the predictions of standard models like maxmin under ambiguous priors, and study their empirical validity. iii) We also analyse different likelihood levels of priors to check for variations in preferences over partial information under ambiguity.

In the next section, we discuss our experimental design. In section 3 we show the connection between some theoretical models of ambiguity aversion and the decisions that participants have to make in the experiment. Section 4 shows the results of the experiment, which are discussed in section 5, and section 6 concludes.

2 Design of the experiment and implementation

The experiment consists of two between-subject treatments (risk and ambiguity).

In each of the treatments subjects are asked to make 20 pairwise choices between lotteries. These lotteries can be of two types: simple lotteries and compound lotteries. Each type of lottery is used to analyse preferences over two classes of choices: simple lotteries represent choices in which all uncertainty is resolved in one period (one-shot resolution); compound lotteries represent choices in which uncertainty is resolved over two periods (gradual resolution).

2.1 Composition of lotteries

In the risk treatment, simple lotteries have two elements: an urn that contains one hundred balls, numbered from 1 to 100, and a subset of these balls, which determine the winning numbers of the lottery.

The first stage of the compound lottery has the same urn as the simple lottery, with balls numbered from 1 to 100. In the first period one ball is drawn from this urn. The content of the urn in the second period depends on the value of this drawn ball. If the value of the ball drawn in the first period is lower or equal to a pre-determined value that we call *threshold value*, then the second stage urn is composed of all balls from the top urn with value equal or lower to the *threshold value*, including the drawn ball. If the ball has a value larger than the *threshold value*, then the second stage urn is composed of all balls with value greater than it. The ball drawn from the second urn determines the prize of the lottery. If the drawn ball coincides with one of the winning numbers, then, the participant wins the lottery prize, otherwise she wins nothing. This is an intuitive and novel way of generating compound lotteries that can easily be understood by subjects in the experiment. Additionally, varying the threshold value and the set of winning numbers, lotteries with same variances but changing skewness can be easily generated.

In the ambiguity treatment, simple lotteries are also formed by an urn, but this urn is composed of two hundred balls. One hundred balls have a value between 1 and 100, whereas the value of the other hundred balls is unknown to both the experimenter and the participant. Each of these unknown values can be a number between 1 and 100. The value of these 100 balls is assigned at the beginning of the experiment using the algorithm developed by Stecher et al. (2011)[6]. This algorithm is designed to generate distributions with no finite moments. This approach, in conjuction with the fact that the experimenter cannot observe the content of the urn until the end of experiment, prevents ambiguity being understood by participants as the experimenter being more knowledgeable about the distribution than themselves (Fox, Tversky, 1995), as past observations of the distribution are not informative about future ones.Neither the experimenter nor the participant learns about the content of the urn until the end of the experiment[7].

Compound ambiguous lotteries are generated similarly to compound risky lotteries. We first determine the *threshold value*, which varies from lottery to lottery. The value of the ball drawn in the first period determines the content of the second urn. If the value of the ball drawn is smaller or equal to the *threshold value*, then the second urn is composed of all balls with value smaller or equal to the threshold value, including the ball drawn. If the value drawn is higher than the threshold value, then the second urn is composed of all balls with value larger than the threshold value.

[6]Participants are informed that the urn is generated at the beginning of the experiment. In our experiment there is no possibility of hedging between choices, but we still follow the prescribed incentive compatible mechanism proposed by Baillon et al. (2014).

[7]Participants are informed about this fact at the beginning of the experiment.

2.2 Choice of lotteries

In both treatments we consider 4 different categories of compound and simple lotteries: 3 lotteries vary in probability or likelihood. Probabilities of winning the prize are either 10%, 50% and 90%. Risky compound lotteries of these categories all have the same variance, that is, the dispersion from the ex-ante probability to the interim probability from receiving the partial information is always the same. This allows us to compare choices between different categories while keeping the informativeness of lotteries constant. One drawback from maintaining informativeness constant for all three probabilites is that changes from the ex-ante probabilities to the interim probabilities are relatively small. This is due to the fact that changes in interim probabilities for very low (10%) and very high (90%) ex-ante probabilities are very constrained from below and above respectively, which limits the set of lotteries that preserve the ex-ante probability and variance. As a way to check whether higher informativeness has a differential effect in preferences, we include an additional set of lotteries, with 50% ex-ante probability, which allows for higher variance in the interim probabilities from the ex-ante probability.

Additionally, in order to study if differences in skewness also affect decision-making, we include one positively and one negatively skewed lottery for each of the four categories.

As mentioned above, participants make 20 pairwise choices between lotteries. These lotteries are completely characterised by the set of winning numbers (for all lotteries) and the threshold value (if the lottery is a compound lottery). The amount of winning numbers pins down the ex-ante probability/likelihood of winning. The number of those winning numbers and the threshold together determine the interim probability of winning, after one of the possible information sets (ball is below or above threshold) has been realised. Different combinations of these two elements lead to positively skewed or negatively skewed lotteries in the risk treatment.

Table 1 shows these two variables, and the characteristic of each lottery.

Lottery #	Set of winning numbers	Threshold value	Description:
1	1-5; 96-100	-	Simple lottery (10%)
2	1-24; 46-71	-	Simple lottery (50%, low variance)
3	16-40; 61-85	-	Simple lottery (50%, high variance)
4	8-97	-	Simple lottery (90%)
5	1-5; 96-100	37	Compound lottery (10 %), positively skewed
6	1-7; 98-100	56	Compound lottery (10 %), negatively skewed
7	1-24; 46-71	45	Compound lottery (50 %), low variance positively skewed
8	25-45; 72-100	45	Compound lottery (50 %), low variance negatively skewed
9	1-15; 41-60; 86-100	20	Compound lottery (50 %), high variance positively skewed
10	16-40; 61-85	80	Compound lottery (50 %), high variance negatively skewed
11	8-97	56	Compound lottery (90 %), positively skewed
12	6-95	37	Compound lottery (90 %), negatively skewed

Table 1: Lotteries in the Experiment

The 20 pairwise choices elicit preferences over early, gradual and late resolution of uncer-

Pairwise choice #	Choice X	Choice Y
1	Early resolution of lottery 1	Late resolution of lottery 1
2	Early resolution of lottery 1	Lottery 5
3	Early resolution of lottery 1	Lottery 6
4	Lottery 5	Late resolution of lottery 1
5	Lottery 6	Late resolution of lottery 1
6	Early resolution of lottery 2	Late resolution of lottery 2
7	Early resolution of lottery 2	Lottery 7
8	Early resolution of lottery 2	Lottery 8
9	Lottery 7	Late resolution of lottery 2
10	Lottery 8	Late resolution of lottery 2
11	Early resolution of lottery 3	Late resolution of lottery 3
12	Early resolution of lottery 3	Lottery 9
13	Early resolution of lottery 3	Lottery 10
14	Lottery 9	Late resolution of lottery 3
15	Lottery 10	Late resolution of lottery 3
16	Early resolution of lottery 4	Late resolution of lottery 4
17	Early resolution of lottery 4	Lottery 11
18	Early resolution of lottery 4	Lottery 12
19	Lottery 11	Late resolution of lottery 4
20	Lottery 12	Late resolution of lottery 4

Table 2: Choices in the Experiment

tainty, for different ex-ante probabilities/likelihoods and skewness by combining the 12 lotteries described in table 1. As can be seen in table 2, for each probability/likelihood level there are 5 pairwise choices: the first choice is between early and late resolution of uncertainty, the second and third ones between early resolution and gradual resolution with a positive and negative skew respectively, and the fourth and fifth ones between late resolution and gradual resolution with a positive and negative skew respectively.

Due to the admittedly complicated nature of computing interim probabilities of winning these lotteries, we compute these probabilities for the participants and show them these probabilities below the lotteries (see figure 4 and Appendix for examples). We also show them the probability of reaching each information set. In the case of the ambiguity treatment we show the lowest and highest probability of the ex-ante probability and the interim probabilities (for cases in which the ball drawn is lower than the threshold and when it is higher) of winning the lottery, as well as the lowest and highest probability of any given information set occurring.

Additionally, all gradually-resolved lotteries lead to the same updating of probabilities under multiple prior models (maxmin, maxmax, α-maxmin) for the two most common Bayesian updating rules in the literature (Gilboa and Marinacci, 2016): *maximum likelihood updating*[8] and

[8]Formally, the updated probability, for realised event A under *maximum likelihood updating* is : $C_A^{ML} = \left\{ P(\cdot|A) | P \in \arg\max_{Q \in C} Q(A) \right\}$, where C is a set of priors over the state of the world and Q is a subset thereof, that represents the marginal prior probabilities of event A.

full-Bayesian updating[9]. The first rule establishes that decision-makers only update the priors that maximise the likelihood of the interim event happening. In our experiment this event is whether the first ball drawn has a number above or below the threshold. The second rule updates all priors considered. Under multiple prior models, decision-makers either consider the prior that minimises their utility (in the maxmin model), maximises it (in the maxmax model), or a convex combination of these two (in the α-maxmin). The priors that minimise (or maximise) utility in this case are the priors that assume the lowest (highest) number of winning numbers among the 100 balls with unknown number. Out of all these priors the maximum likelihood rule establishes that only those priors with the highest number of balls that are below (above) the threshold will be considered, if participants are told that the first ball drawn is indeed below (above) the threshold. Out of all these priors, the prior that will minimise (maximise) the interim probability is the one that has the highest number of balls below or above the threshold (depending on the event), but at the same time considers all these balls as loser (winner) numbers. The posterior generated this way will coincide with the full-Bayesian updating posterior, as in this case again, the lowest (highest) interim probability of winning is the one in which the highest possible number of balls are below or above the urn, and at the same time they are all losing (winning) numbers. Therefore, in this experiment choices cannot be affected by the updating rule, if participants consider multiple priors and we assume that the satisfy one of the most common Bayesian updating rules.

2.3 Timing of experiment

Table 2 shows that the same lottery can be chosen to be resolved early or late. The aim of this pairwise choice is to analyse how the timing of the resolution of uncertainty affects decision-making. In order to effectively test this, the timing of when decisions are made and resolved is explained in detail to participants in the instructions of the experiment. Participants are also told that lotteries resolved early will be played right after all 20 pairwise choices have been shown to participants and that lotteries resolved late will be resolved 30 minutes after all choices have been made[10]. The first part of the gradually resolved lotteries is resolved at the same time as the lotteries resolved early, and the second part at the same time as the lotteries resolved late. We also tell participants that even if they choose to resolve a lottery early, and that lottery is played for money, they will stil have to wait 30 minutes for the experiment to conclude. This rules out the time cost of taking part in the experiment causing any strict preferences for early

[9]Formally, the updated probability under *full-Bayesian updating* for realised event A, and given a prior P about the state of the world in the set of priors C is : $P_A^{FB} = \{P(\cdot|A)|P \in C\}$.

[10]We follow standard waiting time of 30 minutes to allow sufficient time between early and late resolution, following the work by Masatlioglu (2017) and Nielsen (2020).

resolution over either gradual or late resolution. As part of the instructions, participants are also told that, during the 30 minutes between the times in which lotteries can be resolved, they will either be constantly reminded by the prize they won (if an early-resolved lottery is played) or lottery that will be played in 30 minutes (if a gradually resolved or late-resolved lottery is played). They are reminded about this through a small box on the lower right-hand side of their screen[11].

After the instructions, they have to answer a set of questions to show they have understood how lotteries are formed and how they are resolved. Then, participants are shown the 20 pairwise choices in four different orders (see Appendix)[12].

One of the pairwise choices is then randomly selected and one of the three decisions from the selected pairwise choice is also randomly chosen to be played for money by the computer. This method has been determined to be incentive-compatible under the standard assumption of monotonic utility over monetary prizes (Azrieli et al., 2018).

Depending on the choice made by the participants in the randomly selected decision the lottery will be either played by the computer and the outcome shown to participants (if chosen lottery is resolved early), partly resolved and the second part of the lottery shown to participants (if chosen lottery is resolved gradually), or no lottery will be resolved (if chosen lottery is resolved late). In the case of gradually resolved lotteries in the ambiguity treatment, they are not told about the exact value of the drawn value, to maintain participants agnostic about the content of the urn, and prevent updating of beliefs about the numbers on the unknown balls. During the following 30 minutes participants have to complete the slider (real effort) task (Gill and Prowse, 2012). This task is part of a separate project, which aims to look at how differences in endowment, increased or decreased chance of having high future earnings as compared to an ex-ante exogenous probability, and the level of uncertainty about the environment motivates or discourages effort. There are 10 rounds (with two practice rounds) of 90 seconds in this section of the experiment. If participants complete this before the 30 minutes are over, they are taken to a waiting screen that shows for how much longer they will have to wait before they can complete the experiment and the same information they have had during this interval.

After 30 minutes have passed, participants whose selected lotteries had still not been played learn the outcome of the lottery. We then perform some control tasks: risk aversion elicitation is done using the BRET method (Crosetto and Filippin, 2013). We measure ambiguity aversion

[11]In an on-line experiment, the possibility of being distracted by external stimuli is increased as we cannot control the environment to the same extent as in a lab experiment. We, therefore, choose to make this information more salient to participants at all times, so that the feeling of unresolved uncertainty is felt more strongly throught the experiment.

[12]This is done to control for possible order effects.

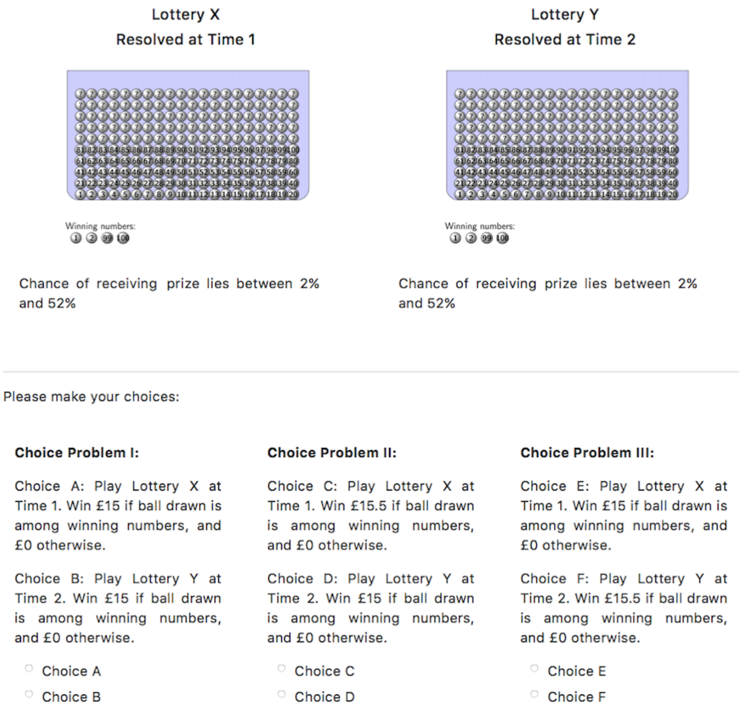


Figure 1: Example of Pairwise Choices and Decisions

using the standard two-urn choice problem of Ellsberg. However, as we want to elicit ambiguity aversion for different likelihoods of winning the prize, we use a risky urn that contains 10 balls numbered from 1 to 10, and an ambiguous urn that also contains 10 balls but where any ball can take any value between 1 and 10. The winning numbers in each of the three decision problems are: 1, 1 to 5 and 1 to 9. This is a standard method used to elicit ambiguity aversion with changing likelihoods of winning (Trautmann, de Kuilen, 2015). We again follow Baillon et al. (2014) and generate the ambiguous urn, which is the same for all three decision problems at the beginning of the experiment. However, due to the risk of suspicion from participants (Hey et al., 2010; Abdellaoui et al., 2015) and possibility of hedging of ambiguity, we chose to pay for all choices in this case. Lastly, we perform a common ratio effect test. This is done to study if a (negative) certainty effect is correlated with preferences over gradual and one-shot resolution of uncertainty, as prescribed by Dillenberger (2010). We also evaluate psychological characteristics of participants with two measures: Big-five personality traits (Rammstedt and John, 2007) and positive and negative affect (Watson et al., 1988).

2.4 Elicitation of strict preferences

As we discussed in section 1, standard expected utility theory establishes that the timing and structure of non-instrumental information should not affect preferences. Therefore, indifference between the choices participants face in the experiment would be compatible with standard models, as neither the independence axiom, nor the reduction of compound lotteries would be violated. Establishing a method to separate strict preferences from preferences that are compatible with indifference is, as a result, necessary to draw conclusions about the validity of the standard and alternative models. We follow the strict preference elicitation method developed by Epstein and Halevy (2019). For each of the 20 pairwise choices, we ask participants to make three decisions, as can be seen in figure 1. In the first one, the prize of the two lotteries is the same (£15), in the second one choice X has a higher prize (£15.5) than Y (£15), and the opposite happens in the third decision. Assuming monotonicity of preferences, if a participant has a strict preference for one of the two lotteries, they would choose that lottery in all three decision problems; if, instead, they only have a weak preference for one of the lotteries, then they would choose that lottery in the first decision problem, and the lottery that gives the highest prize in the second and third lotteries[13].

This preference elicitation method has several advantages: firstly, as we assume that participants do not necessarily satisfy the axioms of (subjective) expected utility (e.g. ambiguity neutrality, reduction of compound lotteries), it prevents issues with eliciting monetary certainty equivalent values of lotteries (Freeman et al. 2019); secondly, due to the high number of decision, and the increased cognitive load this leads to, having only three decisions for each pairwise choice simplifies the experiment compared to other methods of elicitation; thirdly, it simplifies the observation of non-monotonic choices, without imposing them. This is particularly important in an on-line experiment in which participant's attention is one of the main issues compared to lab experiments.

2.5 Implementation

The experiment was run on-line, using oTree (Chen et al., 2016; Holzmeister and Armin Pfurtscheller, 2016) to program it. 121 students from ELFE (Experimental Laboratory of Finance and Economics) at UCL participated in the experiment, between July and August 2020, and were randomly assigned to one of the two between-subject treatments: 61 participants were assigned to the ambiguity treatment and 60 participants were assigned to the risk treatment[14]. The experimental design and main hypotheses were pre-registered at AsPredicted[15]. The average payment was £25.5 (including £5 participation fee). This is in line with laboratory experiments performed at the ELFE lab.

[13]Participants may still have a strict preference over one of the lotteries in this case, if the difference certainty equivalents of the lotteries is smaller than £0.5. Therefore, strict preferences using this method can be interpreted as a lower bound.

[14]The UCL Research Ethics Committee approved the experiment with IRB: 12439/ 001.

[15]AsPredicted is a deposit for experimental designs funded by the Wharton School of the University of Pennsylvania and managed by the Wharton Credibility Lab.

3 Theoretical framework

We now discuss the theoretical predictions of different models of decision-making under risk and ambiguity about the choices over the lotteries we show to participants in the experiment.

We characterise each lottery f as a Savage act f: $\Omega \to X$, a mapping from the set of states of the world Ω to the set of consequences X. In our experiment we can decompose the set of states of the world into two subsets, $\Omega = B \times S$, where $b \in \{1, ..., 100\}$, that is, the realised state within the subset B ($b \in B$) is the ball drawn from the urn that determines the outcome and S is the set of possible compositions of the ambiguous urn, that is, the set of probability distribution over the 100 unknown balls. $x \in \{0, 15, 15.5\}$ ($x \in X$) is the associated prize to the lottery which varies across decision problems, due to the strict preference elicitation method.

We define subsets of the set of the ball that determines the prize B as events or information structures: $E \subseteq B$. In simple or one-shot lotteries the set of events is unique, equivalent to the whole set B, and it is not partitioned further before the realisation of the state of the world; this is so because in these lotteries no further information about the value of the ball is learnt before its realisation. We denote this partition as $\pi_{\varnothing} = \{E_0\} = \{B\}$. In compound or gradually resolved lotteries instead the set of states is partitioned in two events. We denote this partition as $\pi_I = \{E_1, E_2\}$, where $E_1 = \{1, ..., th\}, E_2 = \{th + 1, ..., 100\}$ (where th is the threshold value as shown in table 2), that is, in compound lotteries participants learn if the true state of the world is below or equal to the threshold value, or above it, before they learn b.

3.1 Decision-making under risk

In the risk treatment, we determine the ex-ante probability of winning the lottery in every pairwise choice problem to be the same, that is, for every $b_i \in B$, we enforce that $\Pr(b_i)=p_i$ and $\Pr(E_j)=q_j$ and $\Pr(b_i|E_j)=r_{i,j}$, such that $p_i=\sum_{j=1}^{2} q_j r_{i,j}$. In other words, if subjects satisfy the axiom of reduction of compound lotteries (which implies time neutrality as well (Segal, 1990), then participants should be indifferent between one-shot lotteries and gradually resolved lotteries, and between one-shot lotteries resolved early and late. We can also assume away the subset of states of the world that characterise the distribution of unknown balls as this is completely identified in this treatment (i.e., $\Omega = B$).

However, if the reduction of compound lotteries did not hold [16] we could observe that $f_{\pi_I} \succeq f_{\pi_{\varnothing}}$ or $f_{\pi_{\varnothing}} \succeq f_{\pi_I}$ (where f_{π_I} represents lotteries that are gradually resolved and $f_{\pi_{\varnothing}}$ lotteries that are resolved in one-shot).

[16] Abdellaoui et al. (2015) show a compound-risk premium, which is increasing in the probability of winning lottery. Harrison et al. (2015) find evidence against reduction of compound lotteries.

3.2 Decision-making under ambiguity

In the experiment, we mainly use risky lotteries as a benchmark with which to compare decision-making under ambiguity. We elicit ambiguity generating an urn with 100 balls with unknown values, and 100 balls with a known value . Therefore, Pr(b)$\in \{\frac{1}{200}, ..., \frac{101}{200}\}$, $\forall b \in B$. The exact ex-ante probability depends on the compositions of the urn, which is an element $s \in S$. DM have a set of beliefs about the composition of the urn. These beliefs have been modelled using different models in the literature. Within the framework of our experiment we can reach conclusions about the empirical validity of some of these models. In order to study the implications of each of these models, we consider a monotonic $u : X \to \mathbb{R}$ utility function, and normalise it to u(15)=1 and u(0)=0.

Maxmin utility model (MEU)

This model, first axiomised by Gilboa and Schmeidler (1989), is the most popular model in the literature, mainly due to its simplicity in rationalising the Ellsberg paradox (1961), which is the cornerstone of the literature on ambiguity aversion. It considers a set of priors over the ambiguous state of the world, in this case the composition of the urn, $C \subseteq \Delta(S)$.

The model sets the utility from act $f_{\pi_\varnothing}$ (where a lottery has prize 15) as:

$$V(f_{\pi_\varnothing}) = \min_{p \in C} \sum_{w \in W} p(w) = \min_{p \in C} Pr(win)$$

where $W \subseteq B$ is the set of winning numbers in lottery f.

From our set of lotteries, we can reach the following conclusion.

Proposition 1 *If we assume MEU, all gradually lotteries in table 1 satisfy these two conditions:*

i) $V(f_{\pi_\varnothing}) \geq V(f_{E_1})$

ii) $V(f_{\pi_\varnothing}) \geq V(f_{E_2})$

where $V(f_{E_1})$ *is the value of the lottery after* E_1 *is realised, and similarly for* $V(f_{E_2})$*, with at least one inequality strict for all f in table 1.*

As $Pr(E_1) > 0$ and $Pr(E_2) > 0$ for all $P \in C$, from proposition 1 we conclude that participants have a strict aversion towards all gradually resolved lotteries.

Proposition 1 is implied by Proposition 3 in Li (2020), which states that if a DM has MEU preferences, then she has aversion towards receiving partial information, and this aversion is strict if the set of priors C is not π_1-rectangular, that is, if it is not rectangular with respect to the partition imposed by gradually resolved lotteries. Rectangularity of priors (Epstein and Schneider, 2003) implies that all combinations of conditional and marginal probabilities contained in the set of ex-ante priors are also included in the set of priors. In our case this does not hold. As an illustration, imagine a combination of conditional lotteries where the probability of obtaining the ball 1 is 1/(100+th) after event E_1 (that is, all balls with unknown value have a value below the threshold but different from 1); suppose also a marginal distribution where the probability of state E_1 is th/200 (that is all balls with unknown value have a value greater than the threshold). It is easy to check that a combination of these two leads to a prior that is lower than the lowest ex-ante probability of obtaining 1. Therefore, this set is not rectangular[17].

Therefore, in any event that results from the partition π_1 of the gradually resolved lottery, if participants satisfy MEU, the probability of winning the lottery will be lower than the ex-ante probability, and subjects will therefore have a strict preference for one-shot lotteries.

Choquet expected utility

Choquet expected utility (Schmeidler, 1989) is a representation of preferences in which expected utility is computed using a capacity instead of probabilities. That is, a utility function $V : f \to \mathbb{R}$ is Choquet expected utility if:

$$V(f) = \sum_{\omega \in \Omega} u(f(\omega))v(\omega)$$

where v is a capacity; that is, it is a mapping from the sigma-algebra Σ of states Ω to the interval between 0 and 1 ($v : \Sigma \to [0, 1]$) that satisfies the following conditions:

i) $v(\varnothing) = 0$ and $v(\Omega) = 1$

ii) $E' \subseteq E$ implies that $v(E') \leq v(E)$

Choquet expected utilities can represent ambiguity-averse or ambiguity-seeking attitudes depending on the shape of the capacity v. If v is convex (that is, if $v(E \cup F) + v(E \cap F) \geq v(E) + v(F)$, for any two events E and F in Σ) then they represent ambiguity-averse attitudes and ambiguity-seeking if v is concave (that is, if $v(E \cup F) + v(E \cap F) \leq v(E) + v(F)$).

Choquet expected utilities are a special case of MEU when v is convex (Gilboa and Marinacci (2016)). Therefore, the same results apply as for MEU when the DM is ambiguity averse, i.e., she has a strict preference for the one-shot lotteries over gradually resolved lotteries. Similarly, if v is concave, then Choquet expected utility represents an ambiguity-seeking decision-maker's preferences and as a result gradually resolved lotteries will be preferred to one-shot lotteries.

Multiplier preferences

Multiplier preferences (Hansen and Sargent, 2001) are most commonly used in macroeconomic models. They are characterised by the following utility function:

[17]Formally, a set of priors C is rectangular if $C = \{p \in \Delta(S) : p = \sum_E p^E(\cdot|E)q(E)\ \forall p^E(\cdot), q(E) \in C\}$ where $p^E(\cdot)$ represents the conditional probability after event E and q represents the marginal probability of state E.

$$U(f)=\min_{p \in C}\left[\sum_{w\in W} p(w) + \theta R(p||q)\right]$$

where p is a prior from the set of priors C, as we defined for the MEU model, q is a reference probability measure, R represents the relative entropy of two probabilities measure and θ the degree of ambiguity aversion, and W is defined as above.

Li (2020) uses a model where the reduction axiom is relaxed, and concludes that if decision-makers have the multiplier preferences, then they are indifferent between one-shot and gradually resolved lotteries. This result uses the proof by Strzalecki (2011) about multiplier preferences satisfying Savage's Sure-Thing Principle.

Early vs. late resolution of uncertainty under ambiguity

Strzalecki (2013) using a recursive dynamic model over the timing of resolution of uncertaintiy shows that the only model out of the main models studied in the literature (maxmin, second-order expected utility, smooth model, multiplier model and its generalisation the variational model), only MEU is compatible with indifference to the timing of resolution of uncertainty.

In the next section we analyse the data obtained from the experiment and link the results to the theoretical predictions discussed in this section.

4 Results

In this section we discuss the main results of the experiment. We first focus on comparing one-shot and gradually resolved lotteries across treatments (both between and within subjects). We then analyse preferences between early and late resolution of uncertainty. Lastly, we discuss how strong the preferences expressed in the previous two subsections are.

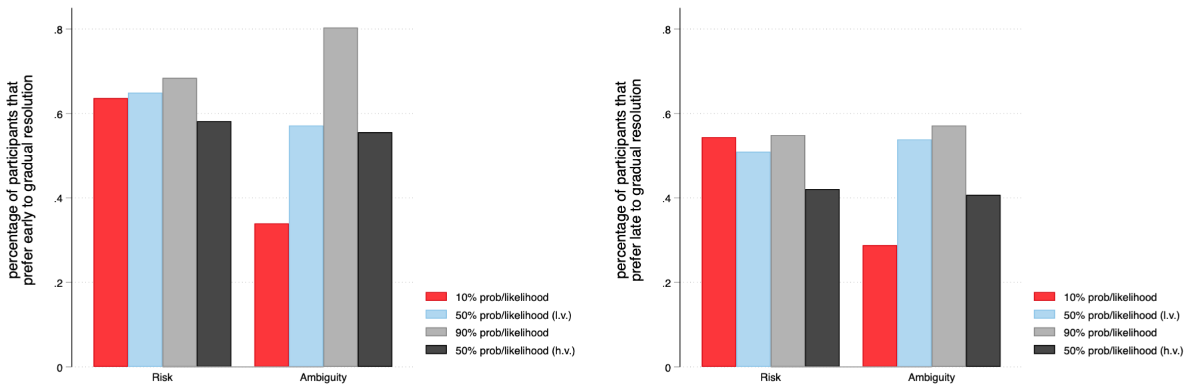
4.1 One-shot vs. gradual resolution of uncertainty

We first analyse the prevalence of preferences between one-shot or gradual resolution of uncertainty in our sample across (between-subject and within subject) treatments. When comparing decisions we exclude observations that do not satisfy the monotonicity axiom[18], but there are no significant qualitative or quantitative differences if we include them. Figure 2 compares the percentages of participants that show a preference for one-shot (either early or late) for

[18] These represent at most 11% of the sample.

positively skewed lotteries[19] [20].

By looking at the figure we can see there is a significant difference in behaviour between treatments. In the risk treatment the percentage of participants that prefer early resolution over gradual resolution remains relatively constant as the ex-ante probability of winning grows, whereas in the ambiguity treatment there is a upward trend, such that approximately only a third of participants choose to resolve the lottery early when the likelihood of winning is low (10%) and 80% choose it when the likelihood of winning is high (90%). Table 3 shows the p-values of McNemar tests on matched choices between early and late resolution of uncertainty for each participant and each pairwise combination of probabilities or likelihoods for risk and ambiguity[21]. They confirm the results from figure 2. The shift from early to gradual resolution of uncertainty as probability increases is not significant under risk, but it is significant under ambiguity.



(a) **(b)**

Figure 2: Percentages of Preferences of Early/Late Resolution over Gradual Resolution

Note: Figure (a) shows the percentage of participants that prefer early resolution of uncertainty over gradual resolution. Figure (b) shows the the percentage of participants that prefer late resolution of uncertainty over gradual resolution. In both cases we consider positively skewed lotteries. “l.v.” stands for low variance and “h.v.” means high variance.

We also use Page’s nonparametric test for ordered alternatives (Abdellaoui et al. (2015)) to test for the existence of a trend in the preference for gradual resolution of uncertainty. The trend is highly significant for ambiguity, both when comparing early and gradual resolution (p-values 0.0001 and 0.0035, for positively and negatively skewed lotteries, respectively) and late and gradual resolution (p-values 0.0077 and 0.0009, for positively and negatively skewed lotteries,

[19] In the ambiguity treatment, skewness can differ depending on the beliefs of participants, but for illustrative purposes we use this term for the corresponding lottery of the positively skewed lottery in the risk treatment, and similarly for the negatively skewed lotteries.

[20] Corresponding graphs for negatively skewed lotteries are in the Appendix.

[21] Corresponding tables for negatively skewed and pairwise comparisons with late resolution of uncertainty can be found in the Appendix.

respectively)[22]. No such trend exists, however, under risk[23].

Risk treatment - Positively skewed lotteries				
	10% probability	50% probability (l.v.)	90% probability	50% probability (h.v.)
10% probability	-	1.000	0.8388	0.3173
50% probability (l.v.)	-	-	0.5930	1.000
90% probability	-	-	-	0.3323
Ambiguity treatment - Positively skewed lotteries				
	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
10% likelihood	-	0.0146**	0.0000***	0.049**
50% likelihood (l.v.)	-	-	0.0192**	0.5485
90% likelihood	-	-	-	0.0029***

Note: Each cell shows the p-values of McNemar test for matched choices between early and gradual resolution of uncertainty under risk for different probabilities. *10% significance level, **5% significance level, ***1% significance level.

Table 3: Test of Significant Shifts Between Early and Gradual Resolution of Uncertainty

From figure 2 we can also notice that there are some differences regarding the choice of early vs. gradual resolution and late vs. gradual resolution of uncertainty. Under ambiguity, the only significant difference is when comparing the pairwise choices that contain 90% likelihood positively skewed lotteries (p-value of McNemar test 0.0047). This, however, does not extend to the choices that contain the negatively skewed lotteries (p-value 0.1967). More importantly, under risk, there is a significant shift of choices from early resolution over gradual resolution to late resolution against gradual resolution for the 50% probability high-variance lottery, for the positively and negatively skewed lotteries (p-values 0.0184 and 0.0325, respectively). In both treatments, there is a significant minority (25% and 21% of the sample, respectively) that shifts from choosing one-shot early lottery to the gradually resolved lottery when faced with the alternative of late resolution. This means that when there is a very large change in probability provided by the additional information, in situations in which participants have to wait, they are willing to receive extra information. However, most participants do not change their preference and can be consistently identified as averse to gradual resolution or gradual resolution loving.

Result 1: *There is a significant differences in attitudes towards the gradual resolution of uncertainty between risk and ambiguity. Under ambiguity, the dominance of this type of resolution is inversely related to the likelihood of winning the lottery. No such trend can be observed under risk.*

[22] We do not include the 50% high variance probability treatment in the test as it is not directly comparable to the other treatments, due to differences in the informativeness of the additional information.

[23] P-values for choice between early or gradual resolution of uncertainty are 0.3832 and 0.1493, for positively and negatively skewed lotteries. P-values for choice between late or gradual resolution of uncertainty are 0.4379 and 0.3832.

4.2 Early vs. late resolution of uncertainty

We now study preferences between early and late resolution of uncertainty for both treatments. Figure 3 shows the percentage of participants that prefer early resolution of uncertainty to late resolution for the two between-subject treatments and the 4 different within-subject treatments. We can see that, contrary to the previous analysis, there is no significant difference between treatments. A large majority of participants (approximately between 70% and 85%, depending on treatment) prefer early resolution of uncertainty over late resolution. Slightly fewer participants have a preference for early resolution of uncertainty under ambiguity. However, this difference is not significant for any within-subject treatment [24].

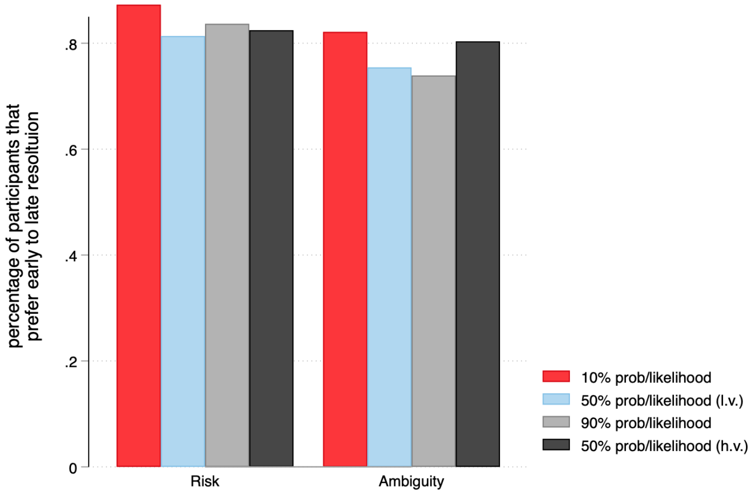


Figure 3: Percentage of Participants that Prefer Early Resolution of Uncertainty over Late Resolution

Note: "l.v." stands for low variance and "h.v." means high variance.

Result 2: *Across all between and within treatments, a large majority of participants prefer to learn the outcome of the lottery early rather than late.*

4.3 Strict preferences

As we mentioned in the Introduction and section 2 indifference between early, late or gradual resolution of uncertainty is compatible with expected utility theory. In order to study if there are deviations from the model we, therefore, also have to take into account if there are strict preference for early or late resolution of uncertainty.

Figure 4 shows the percentage of participants that show a strict preference when asked to choose between early or late resolution of uncertainty (Figure (a)), early or gradual resolution

[24] P-values of Fisher exact test: 0.599 (10% probability/likelihood), 0.502 (50% probability/likelihood, low variance), 0.813 (50% probability/likelihood, high variance), 0.316 (90% probability/likelihood).

of uncertainty (Figure (b)), and late or gradual resolution of uncertainty (Figure(c)). The main takeaway is that there is a big difference in strict preferences between choices that involve the pure time dimension (those in Figure (a)), and those that also involve gradual resolution of uncertainty (Figures (b) and (c)). Between 11% and 27% of participants have a strict preference between early and late resolution of uncertainty. However, between 32% and 61% have a strict preference between early and gradual resolution of uncertainty, and 40% and 57% between late and gradual resolution of uncertainty (see Appendix for details). The shift from weak to strict preferences is significant at 1% for all pairwise comparisons in the ambiguity treatment, and 5% for all comparisons in the risk treatment, except for one, which is significant at 1% (see Appendix).

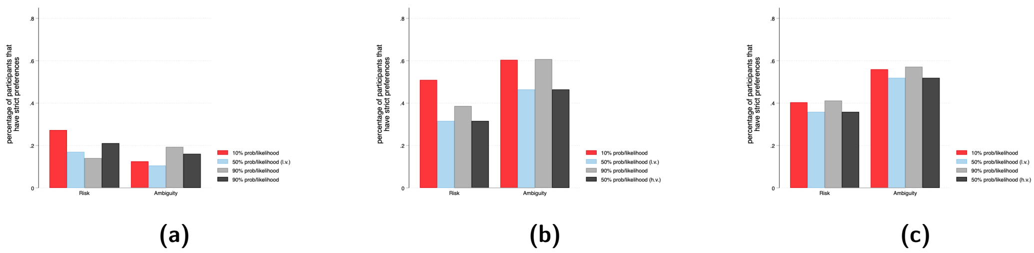


Figure 4: Percentage of Participants with Strict Preferences Across Treatments

Note: Figure (a) shows the percentage of participants that have a strict preference between early and late resolution of uncertainty. Figure (b) shows the the percentage of participants that have a strict preference between early and gradual resolution of uncertainty. Figure (c) shows the the percentage of participants that have a strict preference between late and gradual resolution of uncertainty. In comparisons that include gradually resolved lotteries we consider the positively skewed lotteries. "l.v." stands for low variance and "h.v." means high variance.

It can also be noted that in choices that include gradually resolved lotteries the percentage of participants that have strict preferences is overall lower in the risk treatment than in the ambiguity treatment, although in most cases the difference is not statistically significant, or only marginally significant at 10% (see Appendix).

Result 3: *Approximately half of the sample show a strict preference for or against gradual resolution of uncertainty for all within-subject treatments. Preferences over early or late resolution of uncertainty are much weaker and no more than 20% of the sample has a strict preference over them.*

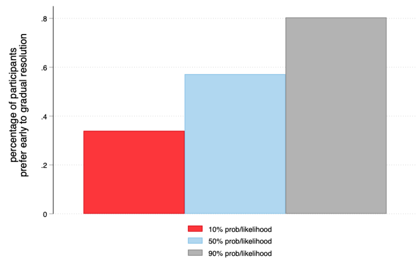
5 Discussion

The results above show that there are significant deviations from the (subjective) expected utility and its predictions about preferences over the timing of uncertainty, both under risk and ambiguity.

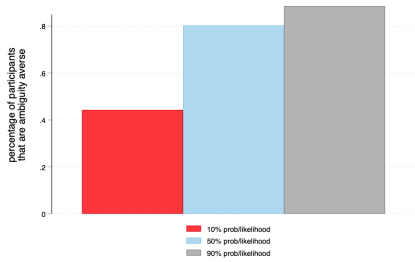
Firstly, at least a third of participants in the experiment have a strict preference over solving uncertainty gradually in both treatments[25]. This is in line with the results from other studies like Nielsen (2020), which find around 40% of participants having a strict preference over the number of periods over which the lottery is resolved. Results also show that there seems to be a difference (albeit only marginally significant) that the strength of preferences is stronger under ambiguity than under risk. We can therefore conclude that a large proportion of the sample (generally more than half in the ambiguity treatment) show preferences consistent with aversion to information that shifts the ex-ante probability or likelihood or a liking for it. There is a significant difference between treatments, however, in terms of the distribution of these preferences. Under risk, this distribution remains quite constant across within-subject treatments, that is, as the probability of winning the lottery goes up there is no significant change in the preferences, and neither is there between more informative and less informative lotteries. This result is in opposition to the main result by Abdellaoui et al. (2015), which finds an upward trend in the preference for simple lotteries as the probability of winning the lottery increases. There are two important differences between our design and theirs, however, that could have influenced the outcome: firstly, they do not take the time aspect into account, that is, compound lotteries are compared to simple lotteries, but they are all solved at the same time. Their elicitation method is also different as they rely on a multiple-price list to estimate a certainty equivalent of lotteries, whereas we have turned to the three decision method developed by Epstein and Halevy (2019).

Secondly, preferences over when lotteries are resolved play a much smaller role in the decision-making process than the number of periods in which the lottery is resolved (no more than 20% of the sample shows a strict preference over early or late resolution of uncertainty). It is possible that the 30 minute interval between both periods is not perceived by subjects to be long enough to generate strict preferences. Additionally, to be the best of our knowledge, this is the first experiment performed on-line that looks into preferences over the timing of information. This may have affected preferences, as the environment and exposure to the outcome of the lottery can significantly affect these preferences (Falk and Zimmermann, 2016). When looking at the distribution of weak preferences, we see that a large majority of participants prefer to learn the outcome of the lottery early rather than late. This result is very different to the result obtained by Nielsen (2020), which states that very few participants choose early resolution of uncertainty. However, there is a big difference in the experimental design, as their design allows for all possible combinations of early gradual or late resolution of uncertainty, and therefore,

[25]Notice that because of the strict preference elicitation method this can be considered only a lower bound on strict preferences



(a)



(b)

Figure 5: Preferences over Gradual Resolution of Uncertainty and Ambiguity Aversion

Note: Figure (a) shows percentage of participants in the ambiguity with a preference for early resolution of uncertainty over gradual resolution. Figure (b) shows percentage of participants in the ambiguity treatment with behaviour compatible with ambiguity aversion

does not directly compare early and late resolution of uncertainty.

In the ambiguity treatment, we observe a trend across likelihoods of winning. This could be explained in terms commonly used in the ambiguity literature as optimism or pessimism towards the composition of the urn. For low likelihoods of winning, participants are more optimistic about the content of the urn and, therefore, are more willing to learn the event before the final outcome as this increases their chances of winning in both events. As the likelihood of winning becomes larger, however, they become more pessimistic and learning about the event before the final outcome lowers the probability of winning. This argument is close to the intuition first used by Ellsberg (2011) about how ambiguity aversion changes across different likelihood choices. This result has been empirically observed in the past, and is also consistent with the results we obtain from the control task where we test ambiguity aversion for different likelihoods events, as can be seen in figure 5. However, these two phenomena seem to be uncorrelated. A Fisher exact test of the correlation between ambiguity aversion and preferences for either early or gradual or late or gradual shows there is no significant correlation in any of the 16 pairwise tests. One caveat is worthing mentioning. Ambiguity aversion is tested using an urn with 10 balls, whereas for the other lotteries we assume an urn with 200 balls. Some theoretical papers (Einhorn and Hogarth, 1985; Rode et al., 1999) explain ambiguity aversion in such a way that it could be interpreted that more complex ambiguity problems may affect ambiguity preferences. In an experimental setting, however, Pulford and Colman (2008) show that this does not seem to alter these preferences. Therefore, these two similar trends seem to be orthogonal to each other.

Theoretical implications

As we discussed in section 3, different models have different prescriptions for preferences over the timing of resolution of uncertainty. With respect to risky choices, we find that the sample is quite evenly split between participants that prefer one-shot resolution of uncertainty and those that prefer gradual resolution of uncertainty. We can state, however, that a non-negligible percentage of participants have a behaviour that is not consistent with standard economic models. We found no significant correlations between these choices and measures like the big-five personality traits and positive and negative affect, that could provide some psychological underpinnings to the observed behaviour, and link it to loss aversion, disappointment aversion or having a preference for suspense or suprise, as proposed by the main papers that provide theoretical explanations for these preferences.

We now turn to study evidence for or against the ambiguity models discussed in section 3.

Results from this section show that under MEU participants should always choose one-shot lotteries over gradually resolved lotteries, and have a strict preference over them. However, we find that only 3 (out of 61) participants show a behaviour compatible with this result. The Choquet model establishes the same result for situations in which participants are ambiguity averse, and that they should have a strict preference for gradual resolution of uncertainty when they are ambiguity-seeking. Only 5 participants satisfy this condition. Finally, the multiplier model establishes that participants should be indifferent between one-shot and gradual resolution of uncertainty. 4 participants satisfy this condition. These three models can, thus, barely account for 20% of the observed choices.

The main reason behind the poor behaviour of these models is that neither the multiplier or MEU model can account for the changing preferences as the likelihood of winning changes. The Choquet model is more flexible as it allows for ambiguity averse and ambiguity seeking attitudes (although the capacity is supposed to be constant for all likelihood levels). But even allowing for changes in the capacity, the Choquet model cannot capture the changes in preferences either, as these are not correlated with ambiguity attitudes. A more realistic model would have to capture the two dimensions (changing ambiguity aversion, changing gradual resolution aversion) at the same time.

6 Conclusion

This paper has focused on studying differences in preferences over the timing of the resolution of uncertainty in situations in which probabilities are known, and those in which they are not known. We find significant deviations from the standard economic model in both cases.

The results can have significant implications in our understanding of these preferences. We find that when the additional information is available about the outcome of the lottery a majority of participants choose to learn it if the ex-ante likelihood of the good outcome is low, but they want to avoid it if the ex-ante likelihood of the good outcome is high. This could, for instance, explain why the take-up of genetic tests is generally low, as the ex-ante probability of having the mutations related to developing these diseases is generally low.

These results could also help to develop information campaigns around individual behaviour related to health or public goods like environmental protection. As we discussed in the Introduction, most information provision has two components (instrumental and non-instrumental). Noticing that under certain circumstances this information may be chosen to be avoided, and as result its instrumental value be neglected, can help design more efficient information mechanisms or better evaluate its welfare-improving value.

There are also gaps in our understanding of the results that would be interesting to look into in future projects. For instance, we still need to understand what makes some subjects more averse to gradual resolution of uncertainty than others, and how to link their behaviour to the alternative explanations provided by the literature. On the theory side, it would be interesting to develop a model that can explain the changes in ambiguity aversion as the likelihood of the good outcome changes, but also how preferences over gradual resolution of uncertainty change as this likelihood varies.

References

[1] Abdellaoui, M., l'Haridon, O., and Zank, H. (2010). Separating curvature and elevation: A parametric probability weighting function. *Journal of Risk and Uncertainty*, 41(1): 39-65.

[2] Abdellaoui, M., Baillon, A., Placido, L., and Wakker, P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *The American Economic Review*, 101(2): 695-723.

[3] Abdellaoui, M., Klibanoff, P., and Placido, L. (2015). Experiments on compound risk in relation to simple risk and to ambiguity. *Management Science*, 61(6): 1306-1322.

[4] Ahlbrecht, M., and Weber, M. (1997). Preference for gradual resolution of uncertainty. *Theory and Decision*, 43(2): 167-185.

[5] Ahn, D., Choi, S., Gale, D., and Kariv, S. (2014). Estimating ambiguity aversion in a portfolio choice experiment. *Quantitative Economics*, 5(2): 195-223.

[6] Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école américaine. *Econometrica*, 21(4): 503-546.

[7] Andersen, S., Fountain, J., Harrison, G., and Rutström, E. (2009). Estimating aversion to uncertainty. Working paper.

[8] Azrieli, Y., Chambers, C., and Healy, P. (2018). Incentives in experiments: A theoretical analysis. *Journal of Political Economy*, 126(4): 1472-1503.

[9] Baillon, A., Halevy, Y., and Li, C. (2014). Experimental elicitation of ambiguity attitude using the random incentive system. Working paper.

[10] Baillon, A., and Bleichrodt, H. (2015). Testing ambiguity models through the measurement of probabilities for gains and losses. *American Economic Journal: Microeconomics*, 7(2): 77-100.

[11] Bellemare, C., Krause, M., Kröger, S., and Zhang, C. (2005). Myopic loss aversion: Information feedback vs. investment flexibility. *Economics Letters*, 87(3): 319-324.

[12] Berger, L., Berger., N., Bosetti, V., Gilboa, I., Hansen, L., Jarvis, C., Marinacci, M., and Smith, R. (2020). Uncertainty and Decision-Making During a Crisis: How to Make Policy Decisions in the COVID-19 Context?. University of Chicago, Becker Friedman Institute for Economics Working Paper.

[13] Bouchouicha, R., Martinsson, P., Medhin, H., and Vieider, F. (2017). Stake effects on ambiguity attitudes for gains and losses. *Theory and Decision*, 83(1): 19-35.

[14] Budescu, D., and Fischer, I. (2001). The same but different: an empirical investigation of the reducibility principle.*Journal of Behavioral Decision Making*, 14(3): 187-206.

[15] Chen, D., Schonger, M., and Wickens, C. (2016). oTree—An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9: 88-97.

[16] Chen, S., and Parmigiani, G. (2007). Meta-analysis of BRCA1 and BRCA2 penetrance. *Journal of Clinical Oncology: Official Journal of the American Society of Clinical Oncology*, 25(11): 1329-1333.

[17] Chew, S., Miao, B., and Zhong, S. (2017). Partial ambiguity. *Econometrica*, 85(4): 1239-1260.

[18] Chu, D., Akl, E., El-harakeh, A., Bognanni, A., Lotfi, T., Loeb, M., Hajizadeh, A., Bak, A., Izcovich, A., Cuello-Garcia, C., Chen, C., Harris, D., Borowiack, E., Chamseddine, F., Schünemann, F., Morgano, G., Muti-Schünemann, G., Chen, G., Zhao, H., Neumann, I., Chan, J., Khabsa, J., Hneiny, L., Harrison,L., Smith, M., Rizk, N., Giorgi-Rossi, P., Abi-Hanna, P., El-khoury, R., Stalteri, R., Baldeh, T., Piggott, T., Zhang, Y., Saad, Z. Khamis, A., Reinap, M., Duda, S. Solo, K., Yaacoub, S., Schünemann, H. (2020). Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. *The Lancet*, 395(10242): 1973-1987.

[19] Conte, A., and Hey, J. D. (2013). Assessing multiple prior models of behaviour under ambiguity.*Journal of Risk and Uncertainty*, 46(2): 113-132.

[20] Crosetto, P., and Filippin, A. (2013). The "bomb" risk elicitation task. *Journal of Risk and Uncertainty*, 47(1): 31-65.

[21] Cubitt, R., Van De Kuilen, G., and Mukerji, S. (2020). Discriminating between models of ambiguity attitude: A qualitative test. *Journal of the European Economic Association*, 18(2): 708-749.

[22] De Filippis, R., Guarino, A., Jehiel, P., Kitagawa, T. (2021) Non-Bayesian Updating in a Social Learning Experiment. *Journal of Economic Theory*, Forthcoming.

[23] Dillenberger, D. (2010). Preferences for one-shot resolution of uncertainty and Allais-type behavior. *Econometrica*, 78(6): 1973-2004.

[24] Dimmock, S., Kouwenberg, R., Mitchell, O., and Peijnenburg, K. (2013). Ambiguity attitudes and economic behavior. Working Paper.

[25] Dimmock, S., Kouwenberg, R., and Wakker, P. (2016). Ambiguity attitudes in a large representative sample. *Management Science*, 62(5): 1363-1380.

[26] Einhorn, H., and Hogarth, R. (1985). Ambiguity and uncertainty in probabilistic inference. *Psychological Review*, 92(4): 433-461.

[27] Eliaz, K., and Schotter, A. (2010). Paying for confidence: An experimental study of the demand for non-instrumental information. *Games and Economic Behavior*, 70(2): 304-324.

[28] Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 75(4): 643-669.

[29] Ely, J., Frankel, A., and Kamenica, E. (2015). Suspense and surprise. *Journal of Political Economy*, 123(1): 215-260.

[30] Epstein, L., and Schneider, M. (2003). Recursive multiple-priors. *Journal of Economic Theory*, 113(1): 1-31.

[31] Epstein, L., and Halevy, Y. (2019). Ambiguous correlation. *The Review of Economic Studies*, 86(2): 668-693.

[32] Epstein, L., and Halevy, Y. (2020). Hard-to-interpret signals. Working Paper.

[33] Evans, J., Skrzynia, C., and Burke, W. (2001). The complexities of predictive genetic testing. *BMJ*, 322(7293): 1052-1056.

[34] Falk, A., and Zimmermann, F. (2016). Beliefs and utility: Experimental evidence on preferences for information. Working Paper.

[35] Fox, C., and Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *The Quarterly Journal of Economics*, 110(3): 585-603.

[36] Freeman, D., Halevy, Y., and Kneeland, T. (2019). Eliciting risk preferences using choice lists. *Quantitative Economics*, 10(1): 217-237.

[37] Gilboa, I., and Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics*, 18(2): 141-153.

[38] Gilboa, I., and Marinacci, M. (2016). Ambiguity and the Bayesian paradigm. In *Readings in Formal Epistemology*, (pp. 385-439). Springer International Publishing.

[39] Gill, D., and Prowse, V. (2012). A structural analysis of disappointment aversion in a real effort competition. *American Economic Review*, 102(1): 469-503.

[40] Gneezy, U., and Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, 112(2): 631-645.

[41] Grant, S., Kajii, A., and Polak, B. (1998). Intrinsic preference for information. *Journal of Economic Theory*, 83(2): 233-259.

[42] Grant, S., Kajii, A., and Polak, B. (2000). Temporal resolution of uncertainty and recursive non-expected utility models. *Econometrica*, 68(2): 425-434.

[43] Gul, F. (1991). A theory of disappointment aversion. *Econometrica*, 59(3): 667-686.

[44] Halevy, Y. (2007). Ellsberg revisited: An experimental study. *Econometrica*, 75(2): 503-536.

[45] Hansen, L., and Sargent, T. (2001). Robust control and model uncertainty. *American Economic Review*, 91(2): 60-66.

[46] Harrison, G., Martínez-Correa, J., and Swarthout, J. (2015). Reduction of compound lotteries with objective probabilities: Theory and evidence. *Journal of Economic Behavior and Organization*, 119: 32-55.

[47] Hayashi, T., and Wada, R. (2010). Choice with imprecise information: an experimental approach. *Theory and Decision*, 69(3): 355-373.

[48] Hey, J., and Pace, N. (2014). The explanatory and predictive power of non two-stage-probability theories of decision making under ambiguity. *Journal of Risk and Uncertainty*, 49(1): 1-29.

[49] Holzmeister, F., and Pfurtscheller, A. (2016). oTree: The "bomb" risk elicitation task. *Journal of Behavioral and Experimental Finance*, 10: 105-108.

[50] Hoy, M., Peter, R., and Richter, A. (2014). Take-up for genetic tests and ambiguity. *Journal of Risk and Uncertainty*, 48(2): 111-133.

[51] Kellner, C., Quement, T., and Riener, G. (2020). Reacting to ambiguous messages: An experimental analysis. Working paper.

[52] Kocher, M. G., Krawczyk, M., and van Winden, F. (2014). 'Let me dream on!'Anticipatory emotions and preference for timing in lotteries.*Journal of Economic Behavior and Organization*, 98: 29-40.

[53] Kőszegi, B., and Rabin, M. (2009). Reference-dependent consumption plans. *American Economic Review*, 99(3): 909-36.

[54] Kreps, D., and Porteus, E. (1978). Temporal resolution of uncertainty and dynamic choice theory. *Econometrica*, 46(1): 185-200.

[55] Lerman, C., Narod, S., Schulman, K., Hughes, C., Gomez-Caminero, A,, Bonney, G., Gold, K., Trock, B., Main, D., Lynch, J., Fulmore, C., Snyder, C., Lemon, SJ., Conway, T., Tonin, P., Lenoir, G., Lynch, H. (1996). BRCA1 testing in families with hereditary breast-ovarian cancer: a prospective study of patient decision making and outcomes. *JAMA*, 275(24): 1885-1892.

[56] Li, J. (2020). Preferences for partial information and ambiguity. *Theoretical Economics*, 15(3): 1059-1094.

[57] Liang, Y. (2021). Learning from unknown information sources. Working Paper.

[58] Lovallo, D., and Kahneman, D. (2000). Living with uncertainty: Attractiveness and resolution timing. *Journal of Behavioral Decision Making*, 13(2): 179-190.

[59] Masatlioglu, Y., Orhun, A., and Raymond, C. (2017). Intrinsic information preferences and skewness. Working Paper.

[60] Nielsen, K. (2020). Preferences for the resolution of uncertainty and the timing of information. *Journal of Economic Theory*, 189, 105090.

[61] Palacios-Huerta, I. (1999). The aversion to the sequential resolution of uncertainty. *Journal of Risk and uncertainty*, 18(3): 249-269.

[62] Pulford, B., and Colman, A. (2008). Size doesn't really matter: Ambiguity aversion in Ellsberg urns with few balls. *Experimental psychology*, 55(1): 31-37.

[63] Rammstedt, B., and John, O. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, 41(1): 203-212.

[64] Rode, C., Cosmides, L., Hell, W., and Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition*, 72(3): 269-304.

[65] Schmeidler, D. (1989). Subjective probability and expected utility without additivity. *Econometrica*, 57(3): 571-587.

[66] Segal, U. (1990). Two-stage lotteries without the reduction axiom. Econometrica, 58(2): 349-377.

[67] Seidenfeld, T., and Wasserman, L. (1993). Dilation for sets of probabilities. *The Annals of Statistics*, 21(3): 1139-1154.

[68] Shishkin, D. r Ortoleva, P. (2021) , Ambiguous information and dilation: an experiment. Working Paper.

[69] Stecher, J., Shields, T., and Dickhaut, J. (2011). Generating ambiguity in the laboratory. *Management Science*, 57(4): 705-712.

[70] Strzalecki, T. (2011). Axiomatic foundations of multiplier preferences. *Econometrica*, 79(1), 47-73.

[71] Strzalecki, T. (2013). Temporal resolution of uncertainty and recursive models of ambiguity aversion. *Econometrica*, 81(3), 1039-1074.

[72] Trautmann, S., and Van De Kuilen, G. (2015). Ambiguity attitudes. In *The Wiley Blackwell Handbook of Judgment and Decision Making*, (Vol. 1, pp. 89-116). Wiley-Blackwell.

[73] Watson, D., Clark, L., and Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. Journal of Personality and Social Psychology, 54(6): 1063-1070.

[74] Zimmermann, F. (2015). Clumped or piecewise? Evidence on preferences for information. *Management Science*, 61(4): 740-753.

Online appendix

A.1 Proofs

Proof of proposition 1

From the main text we know that $V(f_{\pi_\varnothing}) = \min_{p \in C} \sum_{w \in W} p(w)$, and that the minimum probability, without further information, of obtaining one of the winning numbers is $\frac{1}{200}$. Therefore,

$$V(f_{\pi_\varnothing}) = \frac{|W|}{200}$$

where $W \subset B$ is the set of winning numbers in lottery f, and $|W|$ is the cardinality of W.

We can define the utility after E_1 is realised in a similar fashion to $f_{\pi_\varnothing}$.

$$V(f_{\pi_{E_1}}) = \frac{|W_{E_1}|}{100 + th}$$

where $W_{E_1} \subset E_1$ is the set of winning numbers in lottery f after E_1 has occurred, $|W_{E_1}|$ is its cardinality and th is the threshold value in lottery f. The expression above states that lowest probability of winning the lottery after E_1 has occurred is when the numerator is minimised (there is only one ball per winning number in the urn) and the denominator is maximised (all 100 balls with unknown value have value equal or lower than the threshold).

It is easy to see that:

$$V(f_{\pi_\varnothing}) = \frac{|W|}{200} \geq \frac{|W_{E_1}|}{100 + th} = V(f_{\pi_{E_1}}) \iff \frac{|W_{E_1}|}{|W|} \geq \frac{1}{2} + \frac{th}{200}$$

and that this holds for all $|W_{E_1}|$, $|W|$ and th in compound lotteries described in table 1, with strict inequality for all cases but one (lottery 9) where the both sides of the inequality are equal to each other.

Similarly to the case of E_1, we can see that the utility of lottery f after E_2 is realised is:

$$V(f_{\pi_{E_2}}) = \frac{|W_{E_2}|}{200 - th}$$

Therefore,

$$V(f_{\pi_\varnothing}) = \frac{|W|}{200} > \frac{|W_{E_2}|}{200 - th} = V(f_{\pi_{E_2}}) \iff \frac{|W_{E_2}|}{|W|} > 1 - \frac{th}{200}$$

and this also holds for all $|W_{E_2}|$, $|W|$ and th in compound lotteries described in table 1.

A.2 Order of lotteries

The following table shows the four different orders of lotteries used to control for order effects. The numbers used represent number of choice problems as shown in table 2.

Order #	List of choices in order shown
1	[1, 20, 6, 15, 2, 19, 7, 14, 3, 18, 8, 13, 4, 17, 9, 12, 5, 16, 10, 11]
2	[16, 5, 11, 10, 17, 4, 12, 9, 18, 3, 13, 8, 19, 2, 14, 7, 20, 1, 15, 6]
3	[11, 20, 1, 10, 12, 19, 2, 9, 13, 18, 3, 8, 14, 17, 4, 7, 15, 16, 5, 6]
4	[6, 5, 16, 15, 7, 4, 17, 14, 8, 3, 18, 13, 9, 2, 19, 12, 10, 1, 20, 11]

A.3 Experimental instructions

The Experiment

This experiment consists of 3 parts. Each part consists of a set of instructions detailing what is expected of you during that part of the experiment. In the first two parts, this will include a quiz to test your understanding of the questions. You will not be paid according to the answers of the quiz and the exact questions that appear in the quiz will never be asked as part of the choice problems of the experiment. After the instructions and the quiz, you will have to consider some choice problems where you will be paid according to your choices. You will be reminded when the instructions and the quiz have concluded and the choice problems are about to begin. This same sequence of instructions, quiz, and choice problems will occur for the first 2 parts of the experiment.

You will be able to revise the instructions at each page by clicking on buttons at the bottom of the page.

Part 1 - Instructions: Lotteries

(Risk treatment)

In this part of the experiment you will be asked to make choices between different lotteries.

A lottery is a game of chance where the prize depends on the number on a ball drawn from an urn.

-Types of lotteries

During the experiment you will see two different types of lotteries: 1.) *one-stage* lotteries and 2.) *two-stage* lotteries.

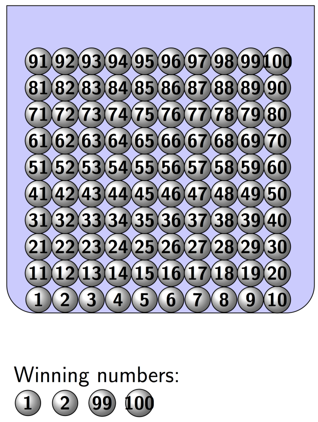
1.) One-stage lottery

A one-stage lottery is a lottery that is resolved after drawing **one** ball from an urn that contains 100 balls.

Below you can see what a one-stage lottery looks like:

Lotteries are composed of two elements, the urn and the winning numbers:

> **The urn:** The urn with 100 balls in total is generated by the computer. Each of the balls have a known number from 1 to 100. None of those balls can have the same number.
>
> **The winning numbers:** To determine whether you win the lottery or not, one ball will be drawn from the urn. If the number on the ball coincides with one of the



winning numbers, then you win the prize of the lottery, otherwise you win nothing. The winning numbers are given and may vary between lotteries.

The winning numbers also determine the chances of winning the prize of the lottery. In the example above there are four winning numbers. This means the chance of winning the prize is 4 divided by 100, which is 4%. These calculations will be provided to you with every lottery before you have to make your choice.

2.) Two-stage lottery

A two-stage lottery is a lottery that is resolved after two draws.

Below you can see what a two-stage lottery looks like:

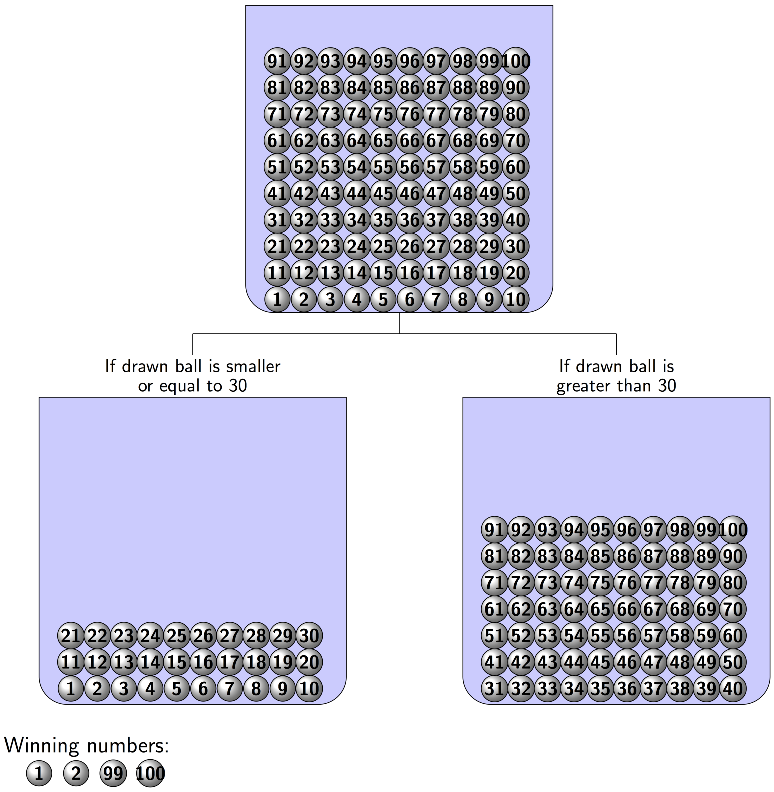
Similarly to the one-stage lottery case, lotteries are composed of two elements, the (three) urns and the winning numbers:

The urns: The first urn for this lottery on top of the figure is created in exactly the same way as the one-stage lottery before. It is generated by the computer and contains 100 balls.

The content of the two urns on the bottom of the figure depends on a value that is pre-determined for each two-stage lottery. This value is called the threshold value. In the example above, the threshold value is 30. This value may be different for each two-stage lottery.

The leftmost urn contains all balls from the urn on top that have numbers smaller or equal to the threshold value. So, in the example above, all balls with a value equal or smaller than 30 are included in the leftmost urn. All remaining balls are included in the rightmost urn.

The winning numbers: As before, a set of winning numbers determines whether you win the lottery or not. Remember that in this type of lottery two balls are drawn.



The first ball is drawn from the top urn. The number on this ball determines from which of the other two urns the second ball is drawn. If the number on the first ball is below the threshold value, the leftmost urn is used to draw the second ball. Otherwise, the rightmost urn is used to draw the second ball.

The chance that the second ball is drawn from either of the urns therefore depends on the threshold value. In the example above, the chance that the second ball is drawn from the leftmost urn is 30%, as there are 100 balls in total and 30 are equal or lower than 30. The chance that the second ball is drawn from the rightmost urn is 70%, as out of the 100 balls 70 are larger than 30, so the chance is 70 divided by 100, i.e., 70%.

The second ball determines the prize. If the number on the second ball coincides with one of the winning numbers, you win the prize. Otherwise, you win nothing. This is the same principle as in the one-stage lottery.

In contrast to the one-stage lottery, you learn some intermediate information about the chance of winning the prize after the first ball is drawn in two-stage lotteries. In the example above, the chance of winning the prize is 4% before the first ball is drawn. This is the same as in the one-stage lottery.

After the first ball is drawn this chance changes depending on the threshold value:

- If a ball lower or equal to 30 is drawn from the first urn, the chance of winning the prize is 2 over 30, i.e., 6.6%, as out of the 30 balls 2 are winning numbers.
- Similarly, if a ball with a number greater than 30 is drawn from the first urn, the chance of winning the prize is 2 over 70, i.e., 2.9%, because from the 70 balls in the urn, 2 are winning numbers.

You will be told about the chance of winning the prize before any ball and after the first ball is drawn at the time of making your choice.

•••••••••••••••••••

(Ambiguity treatment)

In this part of the experiment you will be asked to make choices between different lotteries.

A lottery is a game of chance where the prize depends on the number on a ball drawn from an urn.

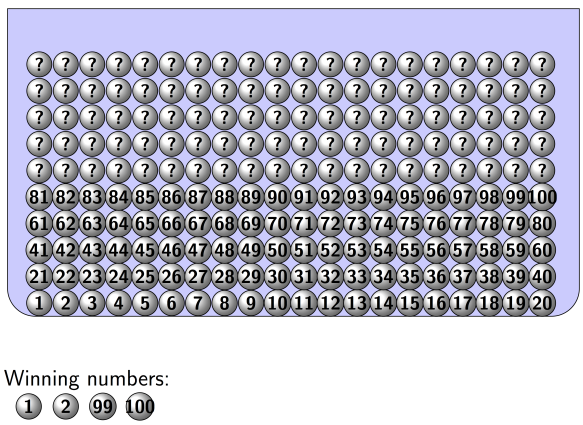
-Types of lotteries

During the experiment you will see two different types of lotteries: 1.) *one-stage* lotteries and 2.) *two-stage* lotteries.

1.) One-stage lottery

A one-stage lottery is a lottery that is resolved after drawing one ball from an urn that contains 200 balls.

Below you can see what a one-stage lottery looks like:



Lotteries are composed of two elements, the urn and the winning numbers:

The urn: The urn with 200 balls in total is generated by the computer. Half of the balls have a known number from 1 to 100. None of those balls can have the same number.

The other half of the balls have an unknown number. These are represented above with a '?' symbol. Each of these 100 balls can have any number between 1 and 100. This means that the same number can be on more than one of those balls. It could also mean that the same number is on all 100 balls or that a number is on none of the balls. The numbers on these balls will be randomly determined by the computer before the first choice problem is shown to you. Neither you nor the experimenter will know the numbers written on these balls until the end of the experiment today. Due to this procedure it is also impossible for the experimenter to guess what the numbers on the balls may be from previous sessions of this experiment.

The winning numbers: To determine whether you win the lottery or not, one ball will be drawn from the urn. If the number on the ball coincides with one of the winning numbers, then you win the prize of the lottery, otherwise you win nothing. The winning numbers are given and may vary between lotteries.

The winning numbers also determine the chances of winning the prize. In the example above there are four winning numbers. Among the 100 balls whose number we can observe four are winning. This means the chance of winning the prize is at least 4 divided by 200 which is 2%. If none of the balls whose numbers we cannot observe have any of the winning numbers, the chance of winning the prize is still 2%. If all of the balls whose number we cannot observe shows any of the winning numbers the chance of winning the prize is 104 divided by 200 which is 52%. So, the chance of winning the prize depends on the number of balls with the ''?' that have the winning numbers. This number can be anywhere between 0 and 100 which means the chance to win the prize will lie between 2% and 52%. These calculations will be provided to you with every lottery before you have to make your choice.

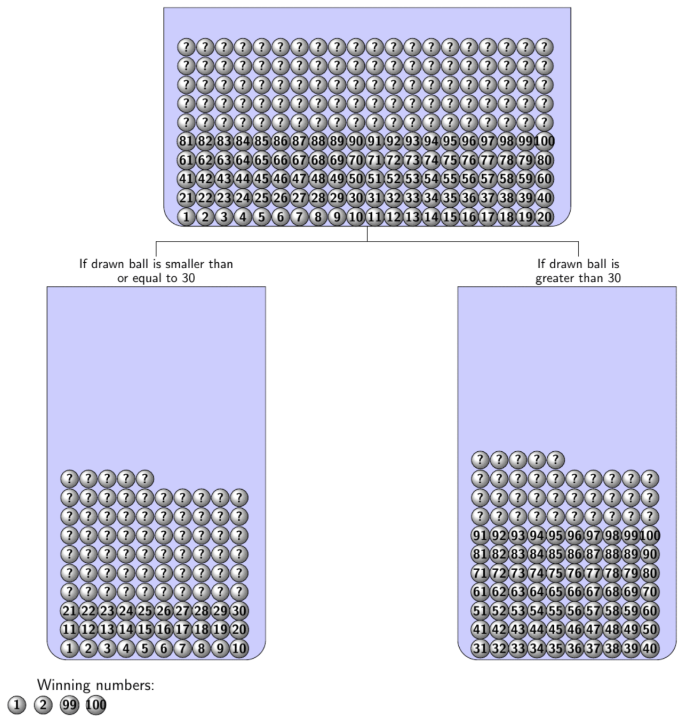
2.) Two-stage lottery

A two-stage lottery is a lottery that is resolved after two draws.

Below you can see what a two-stage lottery looks like:

(Note: In the actual experiment, the figure below was animated, and the 100 balls with unknown number moved back and forth between the two lower urns. We used this so that participants would have a graphical representation of the uncertainty about the content of these two urns. The animated version of the figure can be found at https://elfeexpjulenstatic.s3.amazonaws.com/example_compound_blue_amb.gif*.)*

Similarly to the one-stage lottery case, lotteries are composed of two elements, the (three)



urns and the winning numbers:

The urns: The first urn for this lottery on top of the figure is created in exactly the same way as the one-stage lottery before. It is generated by the computer and contains 200 balls. Again, neither you nor the experimenter will be able to observe the numbers written on the 100 balls with the '?' symbol until the end of the experiment.

The content of the two urns on the bottom of the figure depends on a value that is pre-determined for each two-stage lottery. This value is called the threshold value. In the example above, the threshold value is 30. This value may be different for each two-stage lottery.

The leftmost urn contains all balls from the urn on top that have numbers smaller or equal to the threshold value. So, in the example above, all balls with a value equal or smaller than 30 are included in the leftmost urn. This includes the 30 balls that we know have a number smaller or equal to this threshold value and also all balls with the '?' sign that have such a number. All remaining balls are included in the rightmost urn. Those are balls with values we know are larger than 30 and also those with the sign '?' that have a value larger than 30.

The winning numbers: As before, a set of winning numbers determines the prize of the lottery. Remember that in this type of lottery two balls are drawn. The first ball is drawn from the top urn. The number on this ball determines from which of the other two urns the second ball is drawn. If the number on the first ball is below the threshold value, the leftmost urn is used to draw the second ball. Otherwise, the rightmost urn is used to draw the second ball.

The chance that the second ball is drawn from either of the urns therefore depends on the threshold value. If none of the balls with a '?' symbol in the first urn in the example have a number smaller than or equal to 30, the chance that the second ball is drawn from the leftmost urn is 30 divided 100, i.e., 15%. If all of the balls with a '?' symbol have a number smaller than or equal to 30 the chance is 130 divided by 200, i.e., 65%. Since any number of balls with a '?' symbol can have a number smaller than or equal to 30, the chance that the second ball is drawn from the leftmost urn is therefore between 15% and 65%. Similarly, the chance that the second ball is drawn from the rightmost urn is between 35% and 85%.

The second ball determines the prize. If the number on the second ball coincides with one of the winning numbers, you win the prize. Otherwise, you win nothing. This is the same principle as in the one-stage lottery.

In contrast to the one-stage lottery, you learn some intermediate information about the chance of winning the prize after the first ball is drawn in two-stage lotteries. In the example above, the chance of winning the prize lies between 2% and 52% before the first ball is drawn. This is the same as in the one-stage lottery.

After the first ball is drawn this chance changes depending on the threshold value:

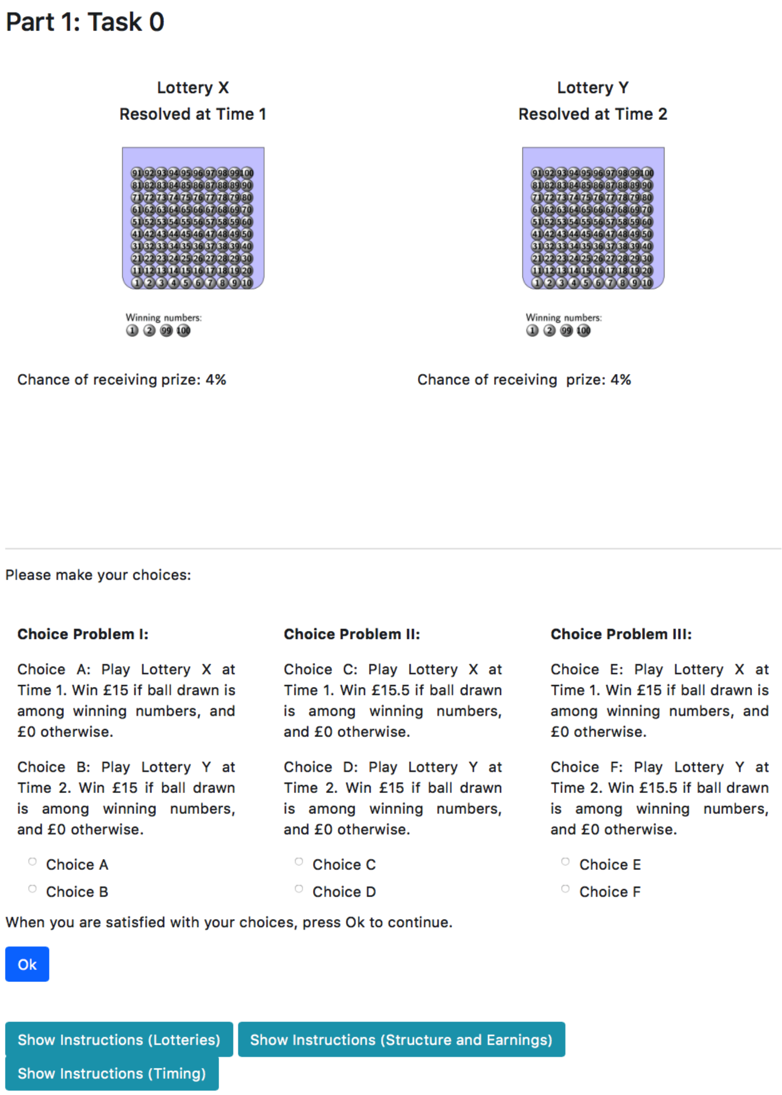
– If a ball lower or equal to 30 is drawn from the first urn, the lowest chance of winning the prize is now 1.5%. This is the case when all the balls with the '?' symbol in the first urn are smaller than or equal to 30 but none of them have the numbers 1 or 2 on them. The chance of winning the prize is then 2 divided by 130 which is 1.5%. The highest chance of winning is 78.5% which is the case if all balls with a '?' symbol from the first urn are smaller than or equal to 30 and show either a 1 or a 2 as 102 divided by 130 is 78.5%. The overall chance of winning is therefore between 1.5% and 78.5% if the first ball shows a number smaller than or equal to 30.

– Similarly, if a ball with a number greater than 30 is drawn from the first urn, the chance of winning the prize lies between 1.1% (if all balls with the '?' symbol are greater than 30, but different from 99 and 100) and 60% (if all balls with the '?' symbol are greater than 30 and have numbers 99 or 100).

You will be told about the highest and lowest chance of winning the prize before any ball and after the first ball is drawn at the time of making your choice.

Part 1- Instructions: Choice tasks

In the first part of the experiment, you will have to complete 20 choice tasks. Here is an example of how each task will look:



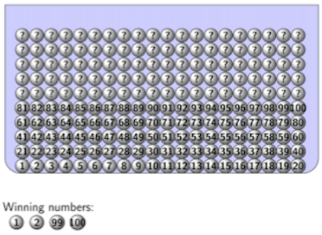
(Risk Treatment)

In each of them, we will show you two lotteries.

You will have to decide which one of the two lotteries you prefer. The two lotteries may differ in three aspects:

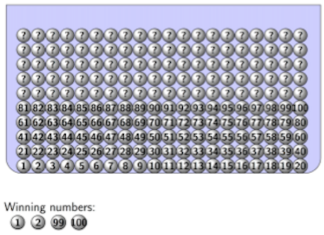
1.) Whether they are one-stage or two-stage lotteries

Lottery X
Resolved at Time 1



Chance of receiving prize lies between 2% and 52%

Lottery Y
Resolved at Time 2



Chance of receiving prize lies between 2% and 52%

Please make your choices:

Choice Problem I:

Choice A: Play Lottery X at Time 1. Win £15 if ball drawn is among winning numbers, and £0 otherwise.

Choice B: Play Lottery Y at Time 2. Win £15 if ball drawn is among winning numbers, and £0 otherwise.

- Choice A
- Choice B

Choice Problem II:

Choice C: Play Lottery X at Time 1. Win £15.5 if ball drawn is among winning numbers, and £0 otherwise.

Choice D: Play Lottery Y at Time 2. Win £15 if ball drawn is among winning numbers, and £0 otherwise.

- Choice C
- Choice D

Choice Problem III:

Choice E: Play Lottery X at Time 1. Win £15 if ball drawn is among winning numbers, and £0 otherwise.

Choice F: Play Lottery Y at Time 2. Win £15.5 if ball drawn is among winning numbers, and £0 otherwise.

- Choice E
- Choice F

(Ambiguity Treatment)

If the lottery is a one-stage lottery, you will learn whether you won the prize or nothing after one ball is drawn. If the lottery is a two-stage lottery, you will learn whether you won the lottery only after the second ball is drawn. However, as we mentioned above, you will learn some extra information about the chance of winning the prize after the first ball is drawn in two-stage lotteries.

2.) The time when a lottery is resolved

A lottery is resolved when the ball that determines the prize is drawn. One-stage lotteries may be resolved at Time 1 or Time 2. This means that you will learn whether you won the prize earlier (if the lottery is resolved at Time 1) or later (if the lottery is resolved at Time 2). Two-stage lotteries are always resolved at Time 2, as the first ball is drawn in Time 1 and the second one is drawn at Time 2. Time 1 happens right after you have made all your choices. Time 2 happens 30 minutes after you have made all your choices. You can see when the lotteries are resolved under the name of each lottery.

For instance, if you choose a lottery that is resolved at Time 1 you will learn whether you won the prize or not right after you have made all your choices and the lottery that will be played for payment is determined (more on this later). If, instead, you choose a lottery that is resolved at Time 2 you will only learn whether you won the prize 30 minutes after that.

3.) The prize of the lottery

In each task you will have to choose three times between the two different lotteries. We will call each of these three choices a choice problem to distinguish them from the 20 choice tasks.

In each of the choice problems the prizes will be different:

• In the first choice problem, the prize is £15 in both lotteries, i.e., you will earn £15 if the ball that determines the prize is equal to one of the winning balls. Otherwise, you will earn £0.

• In the second choice problem, the prize is £15.5 in the first lottery and £15 in the second lottery.

• In the third choice problem, the prize is £15 in the first and £15.5 in the second lottery.

Within each choice task the two lotteries will coincide in two aspects:

1.) The chance of winning the prize before any ball is drawn.

Both lotteries will have the same chance of winning the prize before any ball is drawn. You will be informed about the chance of winning the prize in every choice task. In two-stage lotteries, you will also learn what the chance of winning the prize are after the first ball has been drawn depending on whether the first ball drawn has a number below or above the threshold value.

2.) The set of winning numbers.

The winning numbers which would give you the prize are the same in both lotteries.

Please be aware that there are no right or wrong answers to any of the choice problems. We are trying to learn about your preferences so you should always choose what you personally prefer.

Also keep in mind that your choices will be relevant for your payment today. Therefore, your choices should only be guided by your own preferences.

Part 1 Earnings

One of the 20 choice tasks will be randomly selected by the computer, and one of the 3 choice problems from that choice task will also be selected by the computer. All of these tasks and problems will be equally likely to be chosen by the computer. The lottery you have chosen from the choice problem picked by the computer will be played for payment, and depending on the outcome of this lottery you will either win or lose the prize and this will be added to your final payment.

Part 1- Instruction: Timing of experiment

(Risk treatment)

1.) Quiz

After you have finished reading these instructions you will have to take a short quiz on the content of these instructions. The aim of the quiz is to make sure you have correctly understood the instructions.

2.) Choice tasks

Once you have correctly completed all the questions in the quiz you will be asked to make the choices in the 20 choice tasks we have discussed before.

As only one choice task and one choice problem will be played for payment, and all are equally likely to be chosen, you should consider each of them in isolation when making the decision. That is, you should consider each of the choice problems as if they were the ones that are going to be played.

3.) Drawing of lotteries to be played for payment

After you have made all decisions in the choice tasks, the computer will randomly draw the choice task and choice problem that will be played for payment. The lottery you choose in that specific choice problem will be played for real and determines the prize that will be added to your payment. So, for instance, if numbers 4 and 3 are drawn, the lottery you chose in the fourth choice task in the third choice problem, is the one that will be played for real.

4.) Drawing of ball in Time 1

After learning about the lottery that will be played for payment, one ball will be drawn by the computer. If the chosen lottery is a one-stage lottery resolved at Time 1 you will learn whether you won the lottery immediately. If it is a two-stage lottery you will learn whether the number on that ball is larger or smaller than the threshold, and whether the urn from which the second ball that determines the payment is drawn is the leftmost or the rightmost urn. In this case, the exact number of the first ball will be revealed at the end of the experiment to you and the experimenter, at the same time as the number of the second ball.

If the lottery that will be played is a one-stage lottery to be resolved at Time 2 you will simply see this lottery again.

5.) Part 2 Task

In the second part of the experiment you will perform a different task. We will give you the details of this task after the drawing of the ball in Time 1. This task will be completely unrelated to the decisions or outcome of the choice task. However,**while you are performing the task, and until the drawing of the second ball at Time 2 you will be informed of the prize you won after Time 1, if the lottery played was a one-stage lottery resolved at Time 1. You will also be reminded about the lottery that will be played in Time 2 if the lottery chosen to be played for real is a one-stage lottery to be resolved at Time 2, or a two-stage lottery.** This information will be shown in a box in the lower right corner of the screen for the duration of the second task.

This task will have to be performed even if the lottery chosen has been completely resolved at Time 1.

6.) Drawing of ball in Time 2

Exactly 30 minutes after the drawing of the ball in Time 1, the computer will draw a ball from the lottery that was chosen to be played. This ball will be drawn from the single urn if the lottery chosen to be played is a one-stage lottery resolved at Time 2, or from the urn that was selected in Time 1 if the two-stage lottery is played. If the lottery was already resolved at Time 1, you will be reminded of the prize you won.

7.) Final part of the experiment

After the Time 2 drawing of the ball, you will be asked to make some more choices. These choices will be unrelated to the choice task. After you have completed these tasks, you will have to fill in a short survey, and the experiment will conclude.

• • • • • • • • • • • • • • • • • •

(Ambiguity treatment)

1.) Quiz After you have finished reading these instructions you will have to take a short quiz on the content of these instructions. The aim of the quiz is to make sure you have correctly understood the instructions.

2.) Generating urn Right before we show you the first choice task, the content of the urn will be randomly generated by the computer, following the process we discussed before.

Remember that the whole content of the urn will not be shown to you or the experimenter until the end of the experiment.

3.) Choice tasks Once you have correctly completed all the questions in the quiz , and the urns have been generated, you will be asked to make the choices in the 20 choice tasks we have discussed before.

As only one choice task and one choice problem will be played for payment, and all are equally likely to be chosen, you should consider each of them in isolation when making the decision. That is, you should consider each of the choice problems as if they were the ones that are going to be played.

4.) Drawing of lotteries to be played for payment After you have made all decisions in the choice tasks, the computer will randomly draw the choice task and choice problem that will be played for payment. The lottery you choose in that specific choice problem will be played for real and determines the prize that will be added to your payment. So, for instance, if numbers 4 and 3 are drawn, the lottery you chose in the fourth choice task in the third choice problem, is the one that will be played for real.

5.) Drawing of ball in Time 1 After learning about the lottery that will be played for payment, one ball will be drawn by the computer. If the chosen lottery is a one-stage lottery resolved at Time 1 you will learn whether you won the lottery immediately. If it is a two-stage lottery you will learn whether the number on that ball is larger or smaller than the threshold, and whether the urn from which the second ball that determines the payment is drawn is the leftmost or the rightmost urn. In this case, the exact number of the first ball will be revealed at the end of the experiment to you and the experimenter, at the same time as the number of the second ball.

If the lottery that will be played is a one-stage lottery to be resolved at Time 2 you will simply see this lottery again.

6.) Part 2 Task In the second part of the experiment you will perform a different task. We will give you the details of this task after the drawing of the ball in Time 1. This task will be completely unrelated to the decisions or outcome of the choice task. However, **while you are performing the task, and until the drawing of the second ball at Time 2 you will be informed of the prize you won after Time 1, if the lottery played was a one-stage lottery resolved at Time 1. You will also be reminded about the lottery that will be played in Time 2 if the lottery chosen to be played for real is a one-stage lottery to be resolved at Time 2, or a two-stage lottery.** This information will be shown in a box in the lower right corner of the screen for the duration of the second task.

This task will have to be performed even if the lottery chosen has been completely resolved at Time 1.

7.) Drawing of ball in Time 2

Exactly 30 minutes after the drawing of the ball in Time 1, the computer will draw a ball from the lottery that was chosen to be played. This ball will be drawn from the single urn if the lottery chosen to be played is a one-stage lottery resolved at Time 2, or from the urn that was selected in Time 1 if the two-stage lottery is played. If the lottery was already resolved at Time 1, you will be reminded of the prize you won.

8.) Final part of the experiment

After the Time 2 drawing of the ball, you will be asked to make some more choices. These choices will be unrelated to the choice task. After you have completed these tasks, you will have to fill in a short survey, and the experiment will conclude.

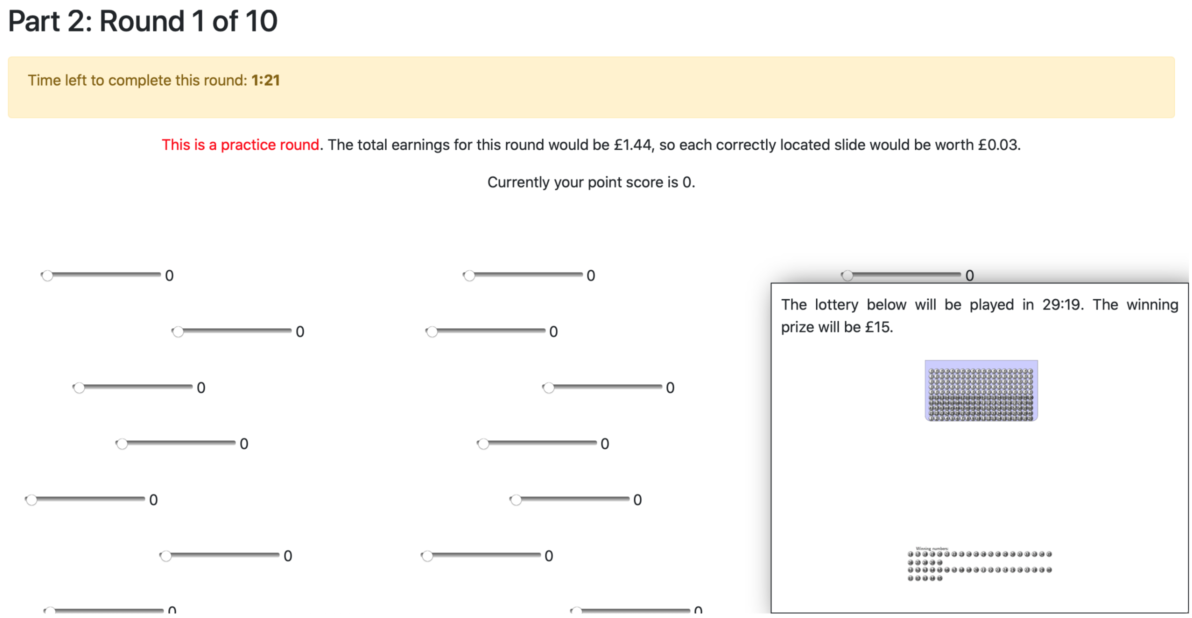


Figure A.1: Example of Slider Task in Ambiguity Treatment

Note: The lottery to be played at time 2 is also shown.

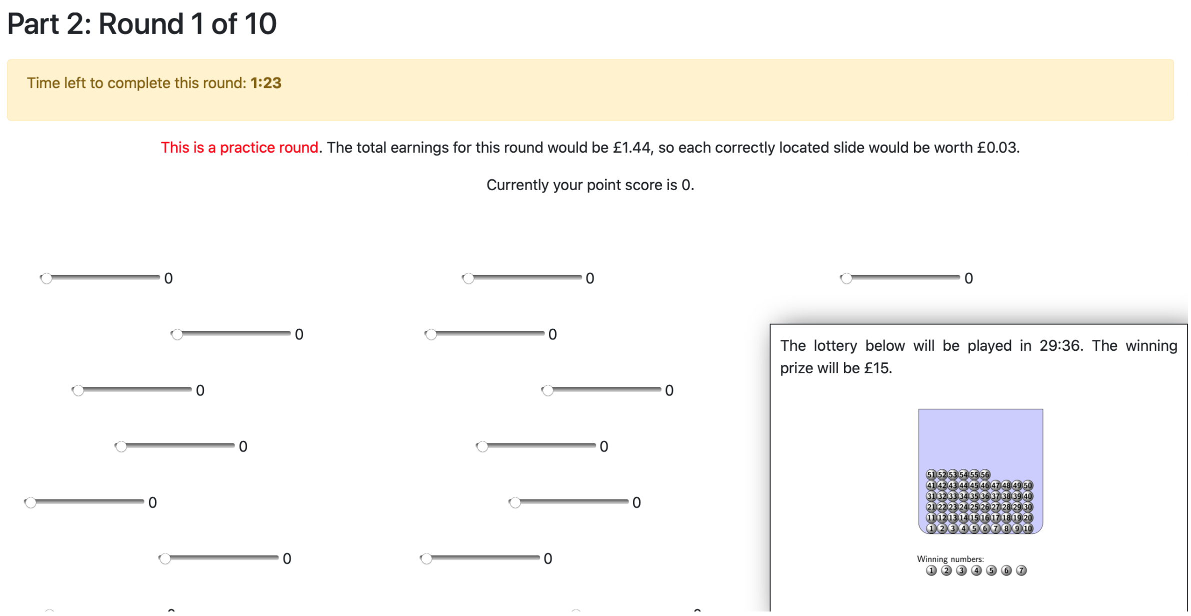


Figure A.2: Example of Slider Task in Risk Treatment

Note: The lottery to be displayed at time 2 is also shown.

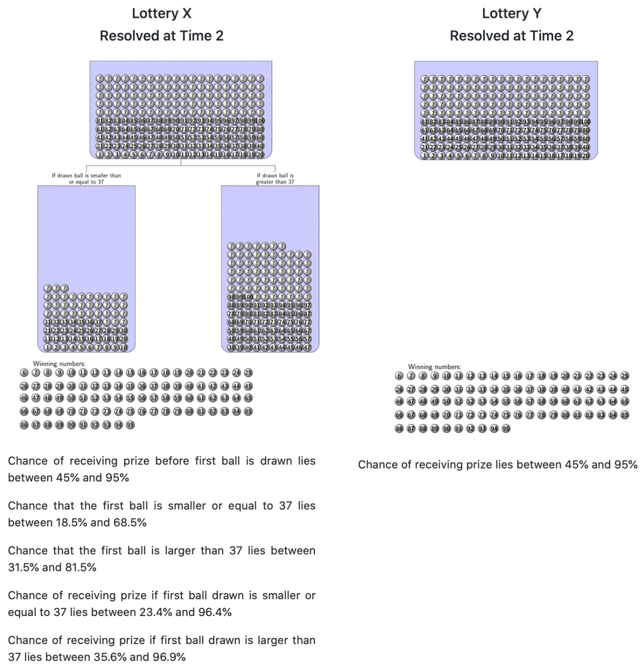


Figure A.3: Example of Lottery Choices in Risk Treatment

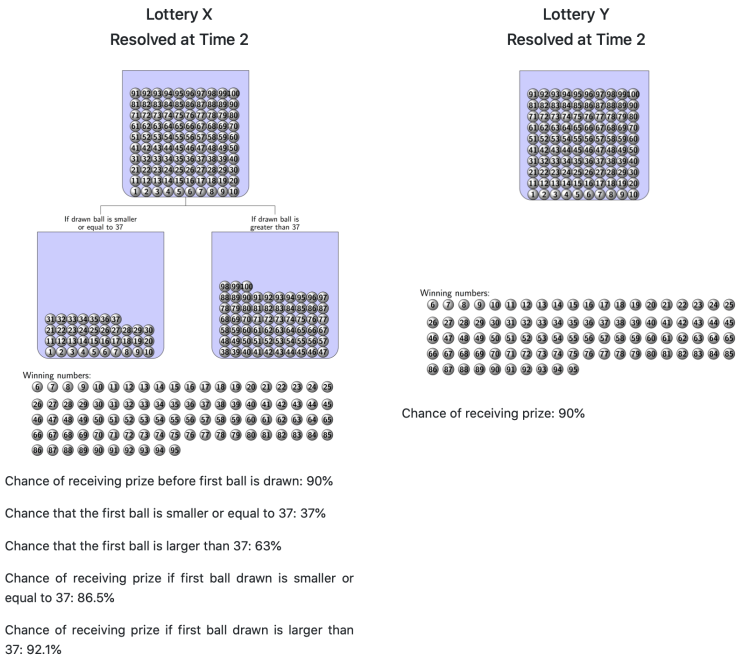


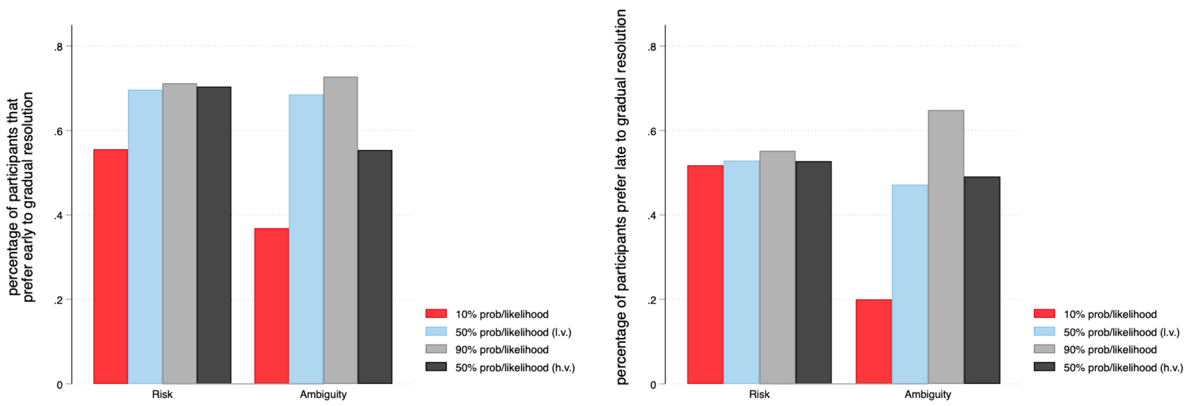
Figure A.4: Example of Lottery Choices in Risk Treatment

	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% l likelihood (h.v.)
Risk treatment - Negatively skewed lotteries				
	10% probability	50% probability (l.v.)	90% probability	50% probability (h.v.)
10% likelihood	-	0.8273	0.6831	0.3173
50% likelihood (l.v.)	-	-	0.5930	0.8084
90% likelihood	-	-	-	0.2253
Ambiguity treatment - Negatively skewed lotteries				
10% likelihood	-	0.0001***	0.0010***	0.0076***
50% likelihood (l.v.)	-	-	0.8185	0.1083
90% likelihood	-	-	-	0.1797

Note: Each cell shows the p-values of McNemar test for matched choices between early and gradual resolution of uncertainty for different probabilities/likelihoods. *10% significance level, **5% significance level, ***1% significance level.

Table A.1: Test of shifts between early and gradual resolution of uncertainty II

A.4 Additional empirical tests



(a) **(b)**

Figure A.5: Percentages of preferences of early/late resolution over gradual resolution (negatively skewed lotteries)

Note: Figure (a) shows the percentage of participants that prefer early resolution of uncertainty over gradual resolution for negatively skewed lotteries. Figure (b) shows the the percentage of participants that prefer late resolution of uncertainty over gradual resolution. In both cases we consider the positively skewed lotteries. "l.v." stands for low variance and 'h.v." means high variance.

Risk treatment - Positively skewed lotteries				
	10% probability	50% probability (l.v.)	90% probability	50% probability (h.v.)
10% probability	-	0.6171	1	0.1025
50% probability (l.v.)	-	-	0.3711	0.2971
90% probability	-	-	-	0.1083
Ambiguity treatment - Positively skewed lotteries				
	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
10% likelihood	-	0.0046***	0.0077***	0.0896*
50% likelihood (l.v.)	-	-	0.3458	0.1967
90% likelihood	-	-	-	0.0389**

Note: Each cell shows the p-values of McNemar test for matched choices between late and gradual resolution of uncertainty under risk and ambiguity for different probabilities/likelihoods. *10% significance level, **5% significance level, ***1% significance level.

Table A.2: Test of shifts between early and gradual resolution of uncertainty III

Risk treatment - Negatively skewed lotteries				
	10% probability	50% probability (l.v.)	90% probability	50% probability (h.v.)
10% likelihood	-	1	0.6547	0.8273
50% likelihood (l.v.)	-	-	0.7963	0.8084
90% likelihood	-	-	-	1
Ambiguity treatment - Negatively skewed lotteries				
	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
10% likelihood	-	0.0028***	0.0001***	0.0082***
50% likelihood (l.v.)	-	-	1	0.0455**
90% likelihood	-	-	-	0.1573

Note: Each cell shows the p-values of McNemar test for matched choices between late and gradual resolution of uncertainty under ambiguity for different likelihoods (negatively skewed lotteries). *10% significance level, **5% significance level, ***1% significance level.

Table A.3: Test of shifts between early and gradual resolution of uncertainty IV

Early vs. late choices problems			
Early vs. late (10%)	0.27		
Early vs. late (50% l.v.)	0.17		
Early vs. late (90%)	0.14		
Early vs. late (50% h.v.)	0.21		
Positively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.51	Late vs. gradual (10%)	0.40
Early vs. gradual (50% l.v.)	0.32	Late vs. gradual (50% l.v.)	0.35
Early vs. gradual (90%)	0.38	Late vs. gradual (90%)	0.41
Early vs. gradual (50% h.v.)	0.36	Late vs. gradual (50% h.v.)	0.44
Negatively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.44	Late vs. gradual (10%)	0.47
Early vs. gradual (50% l.v.)	0.34	Late vs. gradual (50% l.v.)	0.36
Early vs. gradual (90%)	0.47	Late vs. gradual (90%)	0.43
Early vs. gradual (50% h.v.)	0.5	Late vs. gradual (50% h.v.)	0.49

Table A.4: Percentage of participants with strict preferences by probability in the risk treatment

Early vs. late choices problems			
Early vs. late (10%)	0.13		
Early vs. late (50% l.v.)	0.11		
Early vs. late (90%)	0.19		
Early vs. late (50% h.v.)	0.16		
Positively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.60	Late vs. gradual (10%)	0.55
Early vs. gradual (50% l.v.)	0.46	Late vs. gradual (50% l.v.)	0.51
Early vs. gradual (90%)	0.61	Late vs. gradual (90%)	0.57
Early vs. gradual (50% h.v.)	0.52	Late vs. gradual (50% h.v.)	0.52
Negatively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.63	Late vs. gradual (10%)	0.51
Early vs. gradual (50% l.v.)	0.51	Late vs. gradual (50% l.v.)	0.47
Early vs. gradual (90%)	0.65	Late vs. gradual (90%)	0.56
Early vs. gradual (50% h.v.)	0.57	Late vs. gradual (50% h.v.)	0.55

Table A.5: Percentage of participants with strict preferences by probability in the ambiguity treatment.

Prob/likelihood	(1) p-value positive skew/early vs. gradual	(2) p-value negative skew/early vs. gradual	(3) p-value positive skew/late vs. gradual	(4) p-value negative skew/late vs. gradual
		Risk treatment		
10%	0.0029***	0.0330**	0.0290**	0.0719*
50% (l.v.)	0.0389**	0.0253**	0.0116**	0.0593*
90%	0.0047***	0.0001***	0.0016***	0.0006***
50% (h.v.)	0.0201**	0.0002***	0.0186**	0.0011**
		Ambiguity treatment		
10%	0.0000***	0.0000***	0.0000***	0.0000***
50% (l.v.)	0.0001***	0.0000***	0.0000***	0.0001***
90%	0.0000***	0.0000***	0.0003***	0.0011***
50% (h.v.)	0.0001***	0.0002***	0.0001***	0.0003***

Note: Each column (1)-(4) shows p-value of McNemar test of shift in strict preferences from early vs. late choices to early/late vs gradual lotteries, for positively and negatively skewed lotteries and same ex-ante probability/likelihood. *10% significance level, **5% significance level, ***1% significance level.

Table A.6: Test of changes in strict preferences between early/late and early-late/gradual choices

Prob/likelihood	(1) Early vs. late	(2) Early vs. gradual (positive)	(3) Early vs. gradual (negative)	(4) Late vs. gradual (positive)	(5) Late vs. gradual (negative)
10%	0.060*	0.340	0.058*	0.099*	0.708
50% (l.v.)	0.421	0.125	0.082*	0.117	0.324
90%	0.616	0.024**	0.061*	0.123	0.256
50% (h.v.)	0. 0.630	0.124	0.566	0.450	0.703

Note: Each column (1)-(4) shows the exact p-value of the Fisher test of difference in percentage across treatments of participants that have a strict preference over each lottery comparison. *10% significance level, **5% significance level, ***1% significance level.

Table A.7: Test of differences in strict preferences between risk and ambiguity treatment