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Are decision-makers sensitive to the source of uncertainty?

Marielle BRUNETTE* Stéphane COUTURE† Kene BOUN MY‡

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Abstract

Decisions under uncertainty are an integral part of the daily life of economic agents. However, if uncertainty bears on the probability, on the outcome, or on both, it may not be trivial. In this paper, we study how agents react to these different sources of uncertainty. For that purpose, we implemented a lab experiment with 209 students. We mainly show that the way the decision-makers behave when faced with different sources of uncertainty depends on the level of probability of winning a certain outcome. A majority of subjects thus prefers uncertainty to risk, regardless of the source, when the probability is low. For medium and high probability levels, most of the subjects prefers to face uncertainty on the outcome rather than uncertainty on the probability, whereas the opposite is true for low probability levels. Finally, we show that ambiguity preferences have a significant effect on the individual's behavior under all sources of uncertainty, whereas risk preferences play a role only when double uncertainty is at stake.

Keywords: risk, uncertainty, ambiguity, experiments.

JEL classification numbers: C91 (Laboratory, Individual Behavior); D8 (Information, Knowledge, and Uncertainty); D9 (Micro-Based Behavioral Economics)

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1 Introduction

Most of the studies on decision-makers' behavior under uncertainty consider that uncertainty characterizes only the probability of occurrence of the damage.[1] However, the effect of such an assumption on the robustness of the conclusions obtained is never considered, even though the results support public policy or coverage decisions. This strong assumption is not necessarily well founded since, in many decision-making situations, both probability and damage are impacted by noise and are uncertain. Not considering this issue biases the representation of the behaviors studied as well as any subsequent public policy or coverage measures. Moreover, it is recognized that any decision made under uncertainty is strongly conditioned by the risk preferences as well as by the ambiguity preferences of the decision-makers. It then seems necessary to analyze the impact of these different sources of uncertainty on the individual's preferences. This is the challenge of this article. We understand that, in such a context, the knowledge of preferences is fundamental for the adequate understanding of the observed decisions or the anticipation of future decisions in situations where uncertainty is proven.

Uncertainty characterizes many decision-making processes. Indeed, it is not always possible to perfectly know both the probabilities and the outcome associated with an event. For example, a farmer does not precisely know the probability to suffer from a drought and the corresponding damages. In the same vein, a forest owner imperfectly knows the probability that a windstorm will destroy a given forest stand. In these examples, climate change is the driver of the uncertainty. Traditionally, it was possible to estimate the probabilities of a damaging event using historical data. However, in a context of climate change, projecting the historical trend in the future makes no sense since this future is fundamentally marred by uncertainty. This observation is true for other decision-making processes in other fields such as finance, health, etc. Indeed, investors face investment opportunities that often contain vague information about the outcomes, the probabilities, or both. In many situations, measurements and estimates of the two components of risk, probability and outcome, are rarely certain and a noise always remains that can be described as uncertainty. Thus, in many cases that are initially described as risky, the decision-maker faces an uncertain situation. The dimension that is uncertain may differ depending on the situation. In some cases, the probability may be uncertain, in others, the outcome may be uncertain, and sometimes it is both. In this last situation, decision-makers face a double uncertainty that may affect their de-

[1] This situation is commonly referred to as "ambiguity" in decision theory.

cision. Individuals' preferences towards this double uncertainty may be decisive in many decision-making processes, and improving their understanding may be helpful, especially to support public policies.

In this context, we are interested in how individuals deal with different sources of uncertainty: uncertainty on the probability, uncertainty on the outcome and double uncertainty. In particular, we wonder if they prefer to face uncertainty on the probability or uncertainty on the outcome. We also wonder how they react in the face of double uncertainty compared to one-source uncertainty. For that purpose, we implemented an experiment with 209 students where they faced binary comparisons between risk, uncertainty on the outcome, uncertainty on the probability, and double uncertainty. The experiment was decontextualized and based on lottery choices. We also elicited their preferences towards risk and uncertainty through the Multiple Price List (MPL) method proposed by Chakravarty and Roy (2009). The results reveal that: (i) a majority of individuals prefers uncertainty to risk, regardless of the source, when the probability is low; (ii) for medium and high probability levels, most of the subjects prefers facing uncertainty on the outcome rather than uncertainty on the probability, whereas the opposite is true for low probability levels; (iii) ambiguity preferences have a significant effect on the individual's behavior under all sources of uncertainty, whereas risk preferences have an impact only for comparisons implying double uncertainty.

The rest of the paper is organized as follows. Section 2 presents the relevant literature, the research hypotheses and gives some theoretical insights. Section 3 presents the experiment. Section 4 describes the results. Section 5 discusses the results and presents a conclusion.

2 Literature review, hypotheses and theoretical insights

We first present a literature review that leads to the formulation of research hypotheses. Finally, we indicate some theoretical insights.

2.1 Literature review

There is no consensus in the economic experimental literature concerning the impact of uncertainty on outcome versus uncertainty on probability on individuals' decisions. On the one hand, Kuhn et al. (1999) found that uncertainty on the outcome impacts individuals' decisions in a way similar to that of uncertainty on the probability. On the other hand, Schoemaker (1989, 1991) concluded that individuals preferred to solve uncertainty on probabilities rather than uncertainty on outcomes, whereas the opposite was reported by Shapira (1993). In contrast, the results concerning individuals' preferences towards uncertainty seem unanimous: uncertainty aversion for both probabilities and outcomes has been found (Kunreuther et al., 1995; Gonzalez-Vallejo et al., 1996).

In this context, several specific experiments focus on the comparison of multiple sources of uncertainty. To our knowledge, the first experiment was proposed by Du and Budescu (2005). The authors deal with the sources of "vagueness" in an experiment that mimics investment choices. The investment options vary in terms of the sources of vagueness (probabilities and/or outcomes) and domain (gains or losses). In addition, subjects have the opportunity to purchase additional information to increase the precision (*i.e.*, to narrow the width of range) of either the outcome or the probability. They consider two versions. In the pricing version, subjects have to allocate \$100 between the increase in the precision of the outcome or the probability, whereas in the choice version, subjects are asked to indicate if they prefer to increase the precision of the outcome or the probability. They show that individuals avoid vague options and prefer precise ones for comparative pairwise choices in both domains. However, they exhibit a stronger concern for vagueness in the domain of gains than in the domain of losses. Finally, in the pricing version, subjects allocate the \$100 equally between the two options, whereas, in the choice version, they prefer to increase the precision of the outcomes rather than the precision of the probabilities. However, their results are based on a small sample of individuals (64 subjects). In addition, they have an experimental protocol that is contextualized due to the research question addressed and, consequently, the results are difficult to generalize. Moreover, preferences towards uncertainty is a key factor in decision-making under uncertainty, and at the time of the publication of Du and Budescu (2005), an easily implementable elicitation method to quantify uncertainty aversion was not yet available.

Eichberger et al. (2015) introduce the uncertainty on the outcome in the standard two-color Ellsberg experiment. They consider two urns containing each 40 balls, which are either black or red. In urn H, half of the balls are black and the other half red, whereas urn U contains an unknown proportion of black and red balls. To consider uncertainty on the outcome, in addition to uncertainty on the probability, they assume that subjects can win money contained in two envelopes marked with an equal sign or an unequal sign. Subjects have to decide on an urn and a color. A ball is drawn from the chosen urn. If the drawn ball is the chosen color, the subject receives the money in the envelope marked with the equal sign; otherwise, the subject receives the money in the envelope marked with the unequal sign. In doing so, they assume that the two sources of uncertainty are independent of each other. The authors implemented a “paper and pencil” experiment with 119 subjects. They show that few subjects prefer to bet on events with known probabilities once a second source of uncertainty is considered. The authors conclude that this behavior contrasts with the predictions of various theories (MEU, smooth ambiguity), whereas is in keeping with Schmeidler’s CEU approach (Schmeidler, 1989). They underline the necessity of well-defined independence for ambiguity models. They obtained a surprising experimental result, namely that decision-makers faced with this additional uncertainty no longer necessarily have a preference for the situation where the probabilities are known. Theoretically, they show that if decision-makers are averse to ambiguity, then they should always prefer the urn with known probabilities, but they do not separately quantify the uncertainty preferences of decision-makers.

Eliaz and Ortoleva (2015) also consider both sources of uncertainty. However, they assume that the sources of uncertainty are dependent, and they represent this situation through a single urn. They also consider uncertainty on the payment date. For that purpose, they extend the classical Ellsberg paradox to uncertainty on the outcome, double uncertainty (on the outcome and on the probability) and uncertainty on the payment date. They consider an urn with 60 balls, 20 are black, and each of the remaining 40 balls is one of the “uncertain” colors—red or green. Subjects are asked to guess the color of a randomly drawn ball. Participants who guess correctly win \$20 immediately. Now, assume the same urn as above, and as before only a single ball will be drawn, and the participants are asked to choose a color. In one variation, participants are paid only if a black ball is drawn, but they are paid a number of dollars equal to the number of balls in the urn of their chosen color: if X is the number of balls in the urn that are of the color chosen by the participants, they win X if a black ball is drawn. In this case, the probability is not uncertain, because the lottery is paid only if a black ball is drawn, but the amount won is. In another variation, participants are again asked to choose a color, and are paid a number of dollars equal to the number of balls of that color in the urn if a ball of that color is extracted. In this variation, there is a sense in which the uncertainty is on “two dimensions”: not only the likelihood of winning, but also the amount won. In yet another variation, if participants guess correctly, they win X, but are paid X days from the date of the experiment. Here, the authors add uncertainty on a “third dimension”: how soon the prize is paid. Eliaz and Ortoleva (2015) highlight two major conclusions: (i) no uncertainty is preferred to uncertainty on any single dimension and to uncertainty on multiple dimensions; and (ii) “correlated” uncertainty on multiple dimensions is preferred to uncertainty on any single dimension. They are partially in line with the result obtained by Eichberger et al. (2015) that, in a situation where uncertainty cannot be completely removed, decision-makers prefer the situation with several uncertainties to one with only one uncertainty, thus reinforcing the interest of studying behavior under various sources of uncertainty.

More recently, Aggarwal and Mohanty (2021) examined individuals' preferences towards risk and uncertainty considering three sources of imprecise information: uncertainty on the probability, uncertainty on the outcome and conflicting information. Subjects were presented with hypothetical finance investing situations. The article confirms the existing literature that shows an aversion towards uncertainty in comparison to risk. Nevertheless, the magnitude of ambiguity aversion varied with respect to the different sources of ambiguity. However, their results were obtained in a contextualized experiment which limits the generalization of the results. In addition, the authors do not consider the double uncertainty and, the decision-makers did not receive monetary incentives when they participated.

This literature underlines the relevancy to analyze various sources of uncertainty, even if, it might be intuitive to think that, from a theoretical point of view, considering an uncertainty on the outcome could spontaneously be translated as an uncertainty on the probability. The articles mentioned take into account the distinction between sources of uncertainty in mainly applicative approaches (Du and Budescu, 2005; Eliaz and Ortoleva, 2015; Eichberger et al., 2015), showing a framing effect. This cognitive bias causes decision-makers to perceive the two sources of ambiguity differently and then to react differently to decisions depending on how they are presented. The distinction is also considered in theoretical models (Eliaz and Ortoleva, 2015; Eichberger et al., 2015). This underlines the real difference between the two contexts of uncertainty, justifying that different behaviors can be obtained in a framework with uncertainty on the outcome and a framework of uncertainty on the probability. It is therefore important to consider the source of the uncertainty, as theoretical models of decision allow for a wide variety of behaviors. Moreover, from an empirical point of view, the works presented show the possibility of different concerns for the two sources of uncertainty (Du and Budescu, 2005), but also the possibility of highlighting systematic behavioral patterns (Eliaz and Ortoleva, 2015).

Our article is inspired by this literature and contributes to the debate on how decision-makers behave under different sources of uncertainty and how this affects their preferences towards uncertainty. Indeed, we reused the way Eliaz and Ortoleva (2015) implement uncertainty in the experimental protocol but we focus on the analysis of individuals' behaviors in the face of different sources of uncertainty, as well as on the quantification of preferences towards risk and ambiguity in order to highlight the links between these two types of preferences. However, we do not consider uncertainty on the payment date as they do. In addition, we consider three levels for the probability of occurrence of the event: low, medium and high. We increase the size of our sample compared to Du and Budescu (2005) that considers 64 subjects, and we propose a decontextualized experiment.

2.2 Research hypothesis

Based on previous research, we formulate three research hypotheses:

Hypothesis 1: Individuals prefer no uncertainty rather than uncertainty on the probability, on the outcome, or on both.

We want to confirm the results previously obtained (Eliaz and Ortoleva, 2015; Eichberger et al., 2015) that decision-makers always prefer a risky situation to a situation with single or multiple sources of uncertainty. The prediction generally made about the decision-makers' behaviors is that, when confronted with a situation of uncertainty, they always prefer a risky situation. In this article, we would like to ensure the validity of this prediction.

Hypothesis 2: Individuals perceive uncertainty on the outcome and uncertainty on the probability in different ways.

In line with the few previous studies on the subject (Eliaz and Ortoleva, 2015; Eichberger et al., 2015), we assume that decision-makers do not behave in the same way in the presence of uncertainty on the probability of damage as they do in the face of uncertainty on the damage or when both uncertainties exist. Thus, we want to ensure that the source of uncertainty has a significant influence on the behaviour of the decision-maker under uncertainty.

Hypothesis 3: Risk aversion and ambiguity aversion have a significant effect on the decision-makers' behavior under all sources of uncertainty.

The literature (Trautmann and van de Kuilen, 2018; Bühren et al., 2021) found that decision-makers were generally risk-averse and ambiguity-averse in a situation of uncertainty. We plan to quantify these preferences using standard approaches in experimental economics. This will be done in a separate experimental task, independently from the choices under uncertainty that the subjects will face. This quantification will allow us to obtain an accurate measurement of the uncertainty attitude of decision-makers and to classify them as ambiguity-averse, -seeking or -neutral. Indeed, Aggarwal and Mohanty (2021) show that uncertainty preferences must be taken into account and that they significantly influence choices. Preference measures can then be considered as a robust way to explain the heterogeneity of individuals' behaviors under uncertainty.

We test these research hypotheses experimentally. However, it is possible to have a theoretical intuition of expected future behavior and its heterogeneity in the face of different sources of uncertainty, in line with the theoretical decision models on which we rely. We opt for a risky situation in the expected utility framework where the agent transforms the outcome by the utility function, which allows us to consider her aversion to risk, and for an uncertain situation in the smooth ambiguity model (Klibanoff et al., 2005) where the agent has a subjective prior on the subjective probability distribution, as well as a transformation of expected utility, which allows us to consider her aversion to ambiguity.

2.3 Theoretical insights into the observed different heterogeneous behaviors

To our knowledge, there are currently no validated behavioral model to explain observed behavior under uncertainty; however, in the context of the smooth ambiguity model of Klibanoff et al. (2005) (KMM), we know that three factors will be fundamental in explaining the observed behavior of agents: the subjective prior on the subjective probability distribution, the concavity of the utility function U and the concavity of the transformation Φ. According to the situations where the decision-maker is placed, it would be too complicated to bring out a systemic behavior or in any case to identify analytically the conditions on these three factors that would explain the observed behavior. However, it is possible to give an intuition on how all this fits together. In addition, even if we can think that a situation of uncertainty on the probability and a situation of uncertainty on the outcome should lead to the same choice for a decision-maker, we are going to show, from a simple example, how this difference can impact the decision-maker's choice. From a theoretical point of view, there is no a priori reason for systematic behavior to emerge under uncertainty.

To understand how psychological factors of behavior interact and may explain future behavior, let us take a simple example of choosing an urn, focusing on the importance of the a priori distribution in lottery choices under ambiguity. Consider a choice problem represented by three urns:

1. The first urn (denoted R) represents the risk, with two possible outcomes, €0 or €20, each with a probability of 0.5;

2. The second urn (denoted UP) represents uncertainty on the probability, with two possible outcomes, €0 or €20 but where the probability of getting €20 is either 0.4 or 0.6;

3. The third urn (denoted UO) represents uncertainty on the outcome, with an outcome of €0 with a probability of 0.5 and a positive outcome of either €10 or €30 with a probability of 0.5.

These three urns can be considered identical in terms of expected values. It is assumed that the agent has utility over the outcome and has neutrality towards ambiguity. For simplicity, assume that U(0)=0, U(10)=0.5, U(20)=1 and U(30)=1.5.

The decision maker has a prior q in the interval $[0, 1]$ on the probability of winning €20 in the case of the urn 2 (UP) and a prior z in the interval $[0, 1]$ on the low positive outcome in the case of the urn 3 (UO). Under these assumptions, the KMM expected values of the three urns are as follows:

1. $E\Phi(R) = 0.5$

2. $E\Phi(UP) = 0.6 - 0.2q$

3. $E\Phi(UO) = 0.75 - 0.5z$

Also the three KMM expected values of these urns are equivalent if the a priori q and z are identical and if the three situations are perceived in an identical way. If $q = z = 0.5$, then $E\Phi(R) = E\Phi(UP) = E\Phi(UO)$ and the decision maker is indifferent between the three urns. On the other hand, it is possible to find intervals for the a priori for which the decision maker will prefer the uncertain urn to the risky one or for which the uncertain ones are perceived differently. Therefore, it is possible to find both subjective a priori that can explain all possible choices. For example, the decision maker will prefer the urn with uncertainty on the probability if her a priori q is 0.2 (a stronger weight to the probability of 0.6 describing an optimistic character) and that on z of 0.5 (a neutrality on the outcome) to the risky urn and the urn with uncertainty on the outcome.

Also, depending on these subjective a priori and preferences with regard to risk and ambiguity, it will be possible to observe different types of behavior when faced with different situations of uncertainty. Thus, the choices of the decision-makers that we can observe may be very heterogeneous and will depend on their a priori distributions in uncertain situations, which may or may not be symmetrical, on the one hand, and on their perceptions of the different situations, on the other hand. Such behavioral factors and their knowledge will be fundamental and crucial to understand the choices observed in such situations.

3 Experimental design

The study is based on a within-subject laboratory experiment via an online interface (www.econplay.fr). The experiment is broken down into two tasks and completed with a socio-demographic questionnaire. In the first task (Section 3.1), the subjects make binary choices between two lotteries in various contexts in terms of risk and uncertainty (Task 1-A) and, to check the consistency of the subjects' answers, we also ask them their willingness-to-pay to go from one context to another one (Task 1-B: consistency task). In the second task (Section 3.2), we elicit their risk and uncertainty preferences. The last section presents the participants and the procedure (Section 3.3).

3.1 Individuals' choices under risk and uncertainty

In Task 1-A, the subjects make binary choices between two urns (A and B) containing colored balls. At the beginning of the task, subjects choose a color: blue or yellow. This color is then considered as the winning color for the whole experiment. For each decision, subjects choose their favorite urn, *i.e.*, the one they want to play with. Each individual is confronted with four contexts in terms of risk and uncertainty (see Table 1): Risk (R), Uncertainty on the Probability (UP), Uncertainty on the Outcome (UO) and Double Uncertainty (DU). In each of these contexts, the probability and the outcome may be precise or imprecise. These four contexts are initially proposed with a probability fixed at $p = 0.5$. We then consider two additional values (an increase where $p = 0.8$ and a decrease where $p = 0.1$) in order to test the weight given to the risk on the individuals' decisions (see Section 4.3).

A "Precise probability" means that the urn contains precise proportions of balls of

	Probability		Outcome	
	Precise*	Imprecise**	Precise	Imprecise
Risk (R)	X		X	
Uncertainty on the Probability (UP)		X	X	
Uncertainty on the Outcome (UO)	X			X
Double Uncertainty (DU)		X		X

* Precise = known with certainty; ** Imprecise = unknown with certainty.

Table 1: The four contexts in terms of risk and uncertainty and their associated probabilities and outcomes.

each color: 50 balls of the winning color and 50 balls of the other colors corresponding to a probability of 0.5.

An "Imprecise probability" means that the proportion of the balls of each color in the urn is unknown.

A "Precise outcome" means that if a ball of the winning color is drawn from the urn, then the subject wins €20; otherwise, €0.

An "Imprecise outcome" means that if a ball of the winning color is drawn from the urn, then the subject wins an amount between €0 and €40 (with the sure outcome of €20 representing the center of the interval[2]); otherwise, €0.

Figure 1 represents these four different contexts more intuitively.

In this task, the subjects make 16 binary choices. Indeed, the four contexts displayed in Table 1 and Fig. 1 are presented to the subjects two-by-two: R *vs* UO, R *vs.* UP, R *vs.* DU, UP *vs.* UO, UO *vs.* DU. The subjects are exposed to these binary choices three times, one time for each probability level considered: 0.1; 0.5; 0.8. The 16^{th} decision corresponds to the comparison between UP and DU, which is the same choice to be made by the subjects, independently of the level of the probability. These 16 binary choices were randomized to control for potential order effect.

[2]We selected this interval on the basis of the approach used by Gärdenfors and Sahlin (1996). The choice of such an interval is based on the fact that we have the anchor gain of €20 obtained in the risky context and we want to propose a description of the uncertainty on the outcome based on this anchor. In order to introduce the greatest variability in the choice of this interval, we wanted to choose the one with the greatest amplitude in the gains domain only. We choose the largest interval that allowed us to guarantee a subjective expectation and a subjective median identical to the payoff obtained in the risky context.

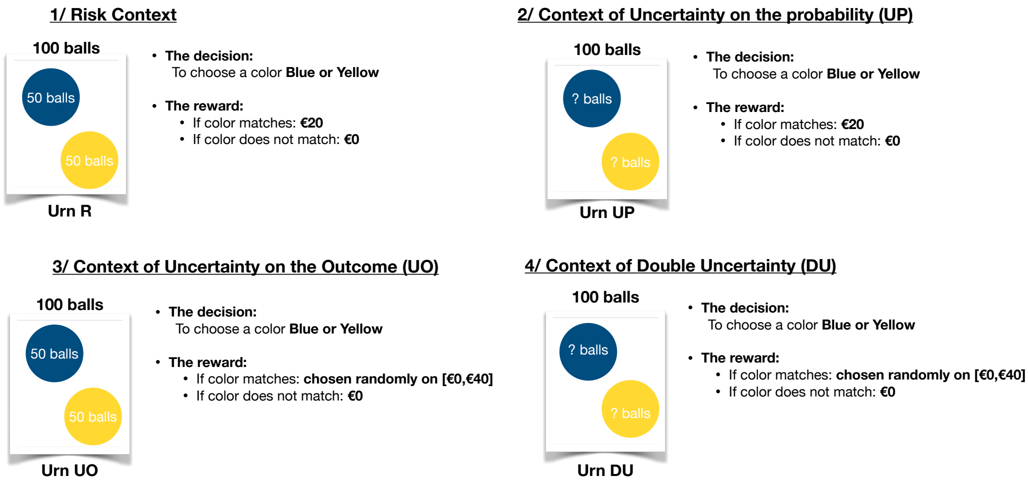

Figure 1: Four decision-making contexts (benchmark : a probability fixed at p = 0.5)

Figure 2 presents an example of decision for a probability of 0.5, a winning color yellow and a choice to be made between *Risk* (Urn A) and *Double Uncertainty* (Urn B).

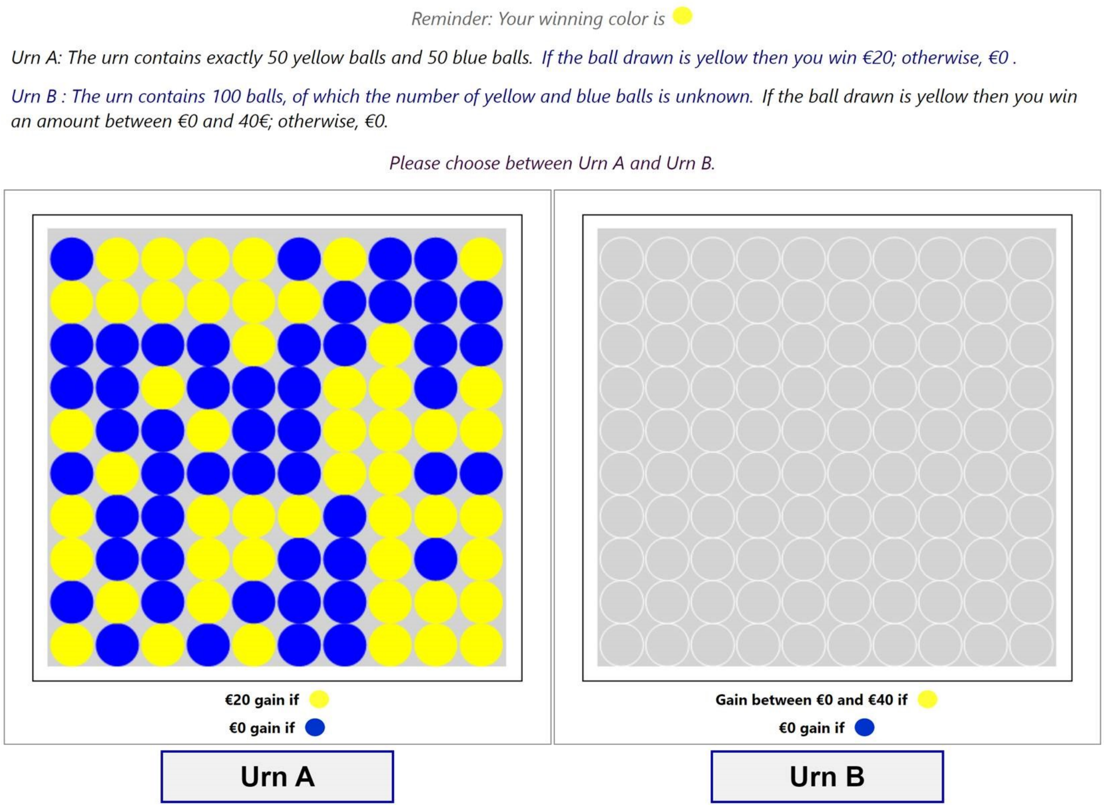

Figure 2: Binary choice with a winning color yellow, a probability of 0.5; Urn A represents *Risk* and Urn B represents *Double Uncertainty*.

To test the robustness of the individuals' choices and to check their consistencies, we also ask the subjects to indicate their willingness-to-pay to go from one context (in terms of risk and uncertainty) to another one (Task 1-B). For this task, Urn B is imposed on the subjects and they have to decide on the amount of money that they are willing to pay to play with Urn A rather than Urn B. The willingness-to-pay belongs to the interval €[0;5] and these amounts appear in a drop-down menu (see Appendix A for a screenshot).

Two different situations may occur:

- Subjects are not willing to pay to switch from Urn B to Urn A. In that case, she selects "0 Euro" in the drop-down menu, and she plays with Urn B.
- The subject is willing to pay to play with Urn A rather than Urn B. In that case, we use the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964). The subject selects one of the positive amounts proposed in the drop-down menu (1, 2, 3, 4 or 5 euros). After that, the computer randomly selects an amount between 1 and €5. If the amount indicated by the subject is greater than or equal to the one randomly selected by the computer, then the subject will play with Urn A, and the cost of this change for the subject will correspond to the amount selected by the computer. If the subject's amount is lower than that of the computer, then the subject will keep Urn B to play at a null cost. For example, if the subject indicates €3 and the computer randomly chooses €2 as the cost for this change, then the subject will play with Urn A and will pay €2 for this switch. On the contrary, if the subject indicates €3 and the computer chooses €4, then the subject will play with Urn B for free.

In Task 1-B, subjects make 19 choices. As in the previous task, the four contexts displayed in Table 1 are presented two-by-two and the following comparison is also added: UO *vs.* UP. Indeed, we don't know if the subjects prefer uncertainty on the outcome or uncertainty on the probability. In that case, we question them on their willingness-to-pay to go from UP to UO, as well as from UO to UP. Subjects make these six binary choices for each of the three probability levels considered. The last decision (here the 19^{th}) corresponds to the comparison between UP and DU. The 19 binary choices were randomized to control for potential order effect.

3.2 Measuring risk and ambiguity aversion

In Task 2, we use a classical Multiple Price List (MPL) method proposed by Chakravarty and Roy (2009), as presented in Fig. 3, to elicit individuals' risk aversion levels. Such a procedure supposes that individuals behave according to an expected utility model and are characterized by a CRRA utility function, classically a power utility function.

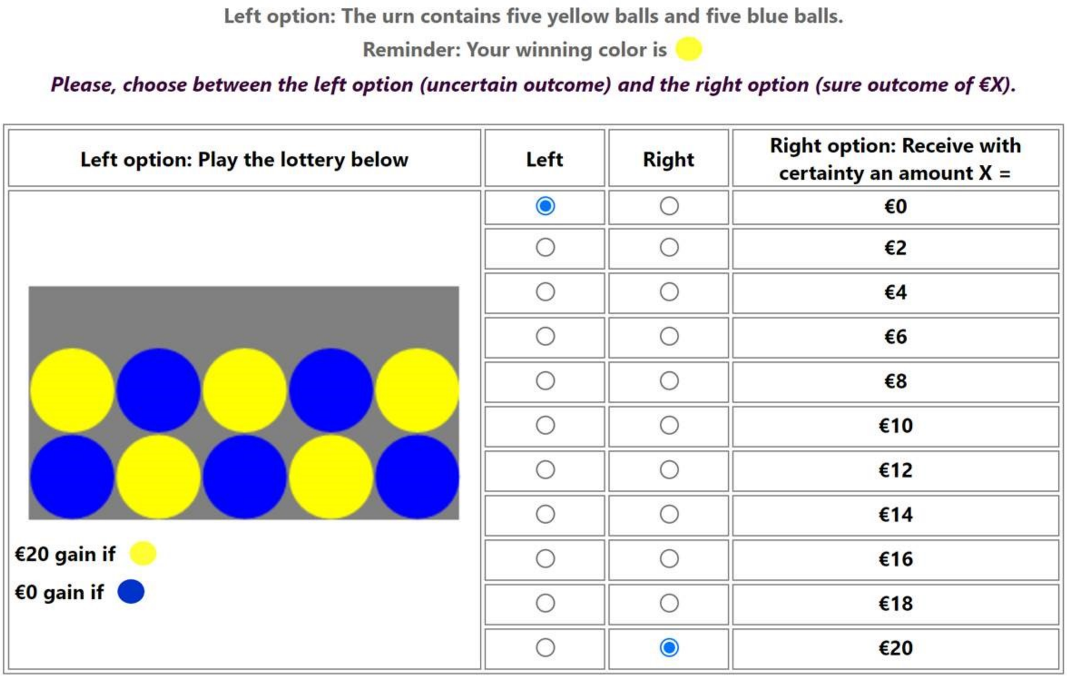

Figure 3: Multiple Price List under *Risk* with a yellow winning color.

The subjects have to choose between two options, left and right. The left option is risky while the right one is safe. The left option consists of drawing a ball from an urn containing five yellow balls and five blue balls. If the ball drawn is the same color as the one designated by the subject as the winning color at the start of the experiment, then the subject wins €20. If the ball drawn is not the same color, then the subject wins €0. The right option guarantees the subject an amount ranging from €0 to €20.

The index of risk preferences is the "switching point", *i.e.*, the number of risky choices. For example, an individual who chooses the left option three times and the right option for the other choices has a switching point of 3. Neutrality appears for a switching point of 5. Consequently, the higher the switching point is, the higher the risk loving will be, and the lower the switching point is, the higher the risk aversion will be. We limit the game so as to have only one switching point, as classically done in MPL methods.

The method to elicit ambiguity aversion is very close to the one used to elicit risk aversion and is similar to Chakravarty and Roy (2009) (see Fig. 4). Again, the subjects have to choose between two options, left and right. This time, the left option is uncertain and the right one is safe.[3] The left option consists of drawing a ball from an urn

[3]Standard approaches quantifying preferences towards ambiguity compare an ambiguous situation

containing yellow and blue balls, but the proportion of the balls of each color in the urn is unknown. If the ball drawn is the same color as the one designated by the subject as the winning color at the start of the experiment, then the subject wins €20. If the ball drawn is not the same color, then the subject wins €0. The right option guarantees the subject an amount ranging from €0 to €20.

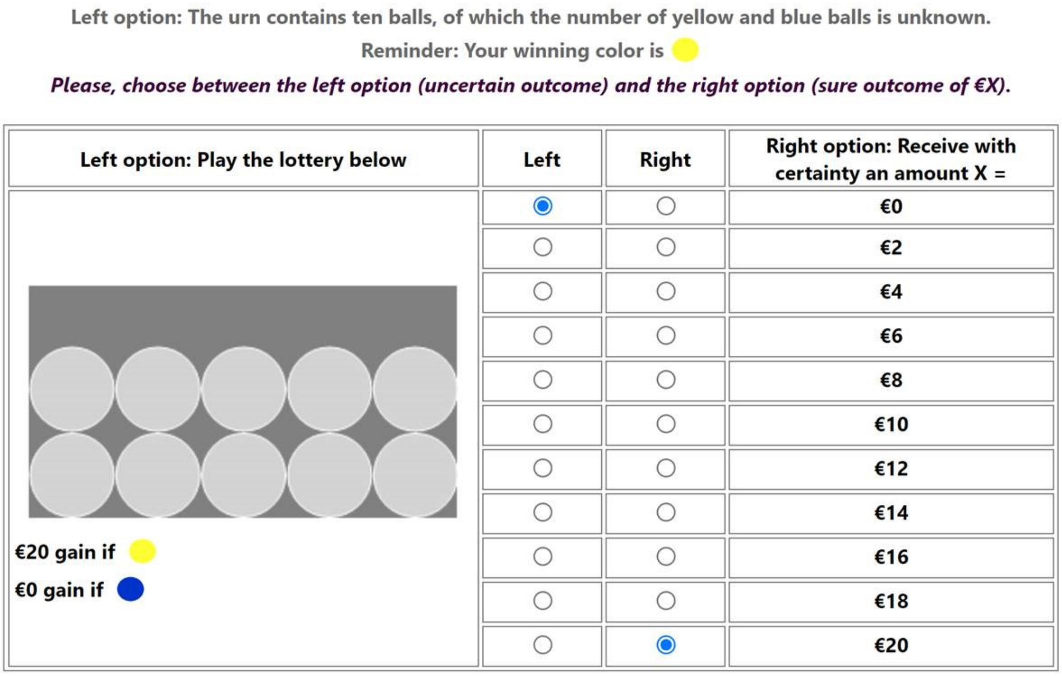

Figure 4: Multiple Price List under *Ambiguity* with a yellow winning color.

As for risk preferences, we retain the switching point as an indicator of the strength of the preferences. The neutrality threshold is also a switching point of 5 (*i.e.*, the number of "ambigous choices"). Consequently, the higher the switching point is, the higher the ambiguity loving will be, and the lower the switching point is, the higher the ambiguity aversion will be. Again, we limit the game so as to have only one switching point.

3.3 Participants and procedure

The experiment was conducted at the Laboratory of Experimental Economics of Strasbourg (LEES) in France in November 2021. A total of 209 students (103 men and 109 women; average age = 21.4 years) participated in the experiment from different study programs. Eight sessions of approximately one hour were run, each with 24 to 28 subjects.

The different tasks of the experiment were incentivized. In Task 1-A, one of the 16

with a risky one. Here, we compare an ambiguous situation and a certain one in order to have an assessment of pure preferences towards ambiguity.

decisions iss randomly selected by the computer at the end of the experiment and played for real. Each of the 16 decisions has the same probability to be selected. The same is true for Task 1-B. One of the 19 decisions is randomly selected by the computer at the end of the experiment and played for real. Each of the 19 decisions has the same probability of being selected. The average of the two outcomes is considered.

In Task 2, one decision is randomly selected, either during the elicitation of risk preferences or during the elicitation of ambiguity preferences. Initially, the computer randomly selects the row that determines the gain. If the subject has chosen the left option for this row, then a ball is drawn from the urn, and if this ball is the winning color, then the subject wins €20; otherwise, the subjects wins €0. If the subject has chosen the right option for this row, then the subject wins the corresponding amount (between €0 and €20).

At the end, the subject receives: the average payoff of Task 1-A and Task 1-B + the payoff associated with Task 2. On average, each subject receives €25.2.

4 Results

We first present the results associated with choice and preference elicitation: Task 1-A and Task 2 (Section 4.1). We then look at the robustness check provided by the results using Task 1-B (Section 4.2), and we present the results of the sensitivity analysis on the probability level (Section 4.3). In Section 4.4, we look for a potential link between the preferences towards risk and ambiguity and the individuals' choices. Finally, we compare the results with our three research hypotheses (Section 4.5).

4.1 Results of choice and preference elicitation

In the choice elicitation Task 1-A, subjects have to make binary choices between each possible combination of the four contexts. The following table presents the results of these choices.

	% A	% B
R - UP	80.4	19.6
R - UO	52.2	47.8
R - DU	69.4	30.6
UP - UO	21.1	78.9
UO - DU	78	22
UP - DU	32.5	67.5

Table 2: Percentage of subjects choosing A and B choices for each binary comparison.

For example, the first row may be interpreted as follows: 80.4% of the subjects choose option A (*i.e.*, risk (R)) and 19.6% select option B (*i.e.*, uncertainty on the probability (UP)). This means that the subjects generally prefer risk to uncertainty on the probability. The results are different functions of the binary choices concerned and some interesting observations can be made. It is then possible to globally classify the four situations tested and to thus identify the preferences of the decision-makers for these four contexts. We are then able to establish a ranking.

First, we can observe that at the macro level R $\sim$ UO $>$ DU $>$ UP, meaning that a majority of the subjects prefer risk to uncertainty on the probability and double uncertainty, whereas they seem to be indifferent to risk and uncertainty on the outcome. We also analyze the micro-level results concerning ranking[4]. From the observed decisions of the 209 subjects, we obtained 78 sequences of three ranking. We also observed 48 sequences of ranking, among the 78 chosen, by only one subject (*i.e.*, 23% of the sample, 48 subjects). Using a threshold of subjects at 15, we identified three key sequences of ranking gathering 22% of the sample (*i.e.*, 46 subjects). Each key sequence of ranking corresponds to one profile of subjects behaving in the same way.

• Key sequence 1 : UP>DU>R>UO (p=10%); R>UO>UP>DU (p=50%); R>UO>UP>DU (p=80%). 15 subjects among 209 (7.2% of the sample) have this sequence of choice. These subjects : i) have the same ranking for medium and high probability levels, and ii) they prefer risk to uncertainty for medium and high probability levels. The 15 subjects following this Key sequence 1 are mainly risk neutral/averse (7/7 on 15).

• Key sequence 2 : DU>UP>UO>R (p=10%); UO>R>DU>UP (p=50%); UO>R>DU>UP (p=80%). 15 subjects among 209 (7.2% of the sample) have this sequence of choice. These subjects : i) have the same ranking for medium and high probability levels, and ii) they prefer the uncertainty on the outcome for medium and high probability levels. The 15 subjects following this Key sequence 2 are mainly risk neutral/lover (5/6 on 15).

• Key sequence 3 : DU>UP>UO>R (p=10%); UO>DU>R>UP (p=50%); UO>R>DU>UP (p=80%). 16 subjects among 209 (7.7% of the sample) have this sequence of choice. These subjects : i) prefer the uncertainty on the outcome for medium and high probability levels; ii) their worst situation is uncertainty on the probability for medium and high probability levels. The 16 subjects following this Key sequence 3 are

[4] The inconsistency of some individuals' choices is analyzed in Appendix B.

mainly risk neutral/lover (4/9 on 16).

The other 55% of the sample are represented by 27 different sequences of ranking gathering between 2 and 9 subjects.

Second, the subjects clearly prefer uncertainty on the outcome (78.9% B choices) rather than uncertainty on the probability (21.1% A choices).

Finally, the last two rows of Table 2 reveal the subjects' behavior towards double uncertainty compared to one-source uncertainty. It is interesting to observe that they prefer uncertainty on the outcome to double uncertainty (78% A choices *vs.* 22% B choices), whereas double uncertainty is preferred to uncertainty on the probability (67.5% B choices *vs.* 32.5% A choices). Such a surprising result has already been observed in the paper of Eliaz and Ortoleva (2015). One major conclusion for this part is that subjects always try to avoid uncertainty on the probability, regardless the binary choices analyzed.

Before explaining these binary choices as a function of behavioral factors, we assess preferences for risk and ambiguity. We now look at the results of the MPL procedure that elicits the subjects' preferences towards risk and ambiguity. The following table presents these results.

Switching point	% Risk	% Ambiguity	Preferences
0-1	8.1	7.7	.
2	1.4	3.8	.
3	3.3	19.6	↑
4	20.1	27.3	Aversion
5	31.6	19.1	Neutrality
6	23.9	9.1	Loving
7	6.7	5.7	↓
8	2.4	3.8	.
9-10	2.4	3.8	.
Average switch	4.93	4.42	

Table 3: Elicitation of preferences: switching point under *Risk* and *Ambiguity*.

Under risk, 31.6% of the subjects are neutral, 35.4% are loving and 33% are averse. The sample is approximately equally split into the three classes. Concerning risk aversion, we can see that most of the subjects have a switching point at 4, close to the neutrality threshold, that switching points 2 and 3 are few selected whereas the extreme risk aversion is well represented with 8.1% of the sample. For risk loving, lots of subjects choose a switching point at 6, close to the neutrality, and that the extreme points, 8, 9 and 10, are very few selected. The average switching point is 4.93, indicating, on average, risk aversion, but in fact, it is very close to neutrality. Moreover, the difference between 4.93 and the neutrality threshold of 5 is not significant ($t = -0.590$; $p = 0.278$).

Under uncertainty, 19.1% of the subjects are neutral, 22.5% are loving and 58.4% are averse. Concerning ambiguity aversion, the subjects have mainly chosen switching points of 3 and 4, close to neutrality. The same comment applies for ambiguity loving, since most of the ambiguity lovers have a switching points of 6 or 7. The average switching point is 4.42 so that, on average, the subjects are uncertainty-averse. This is confirmed by the statistical comparison between 4.42 and the neutrality threshold of 5, which is significant ($t = -4.244$; $p < 0.001$).

A common result in the literature is that decision-makers are risk-averse and ambiguity-averse. In our sample, such conclusions are not as strong. It is clear that subjects are averse to ambiguity, but they seem to be evenly distributed among the three major categories concerning risk preferences: neutral, averse or loving, with about 62% of decision-makers being risk-neutral or risk-averse. The high proportion of risk appetite could be explained by the choice proposed, our student population, and the amount of payoff considered (BounMy et al., 2022).

To go deeper, we analyze the correlation between risk and ambiguity preferences. We find a positive correlation between the distribution of the switching points under risk and under ambiguity (Pearson coefficient = 0.347; $p = 0.001$). This result is consistent with Chakravarty and Roy (2009).

In addition, we studied gender effect since it is common in experimental literature dedicated to risk attitude. We found that gender significantly explains preferences towards risk and ambiguity. More precisely, being a woman has a significant and negative impact on the switching point both for risk ($t=-2.544$; $p = 0.012$) and ambiguity ($t=-2.124$; $p = 0.035$). This means that women are more risk-averse than men, a classical result in the literature (Jianakoplos and Bernasek, 1999; Eckel and Grossman, 2008) and also more ambiguity-averse. Other variables like age, discipline and income have no significant impact.

Finally, knowing the individual's preferences towards risk and ambiguity allows us to refine the analysis provided by Table 2 by category of preferences, as follows.

This table reads as follows: for the binary comparison Risk (R) and Uncertainty

	Risk preferences - % A			Ambiguity preferences - % A		
	Averse (33%)	Neutral (31.6%)	Loving (35.4%)	Averse (58.4%)	Neutral (19.1%)	Loving (22.5%)
R - UP	59.3	61.2	60.4	61.5	62.5	55.3
R - UO	53.9	47.8	38.3	53.8	48.3	25.5
R - DU	60.3	56.7	52.3	59	56.7	48.9
UP - UO	39.7	37.3	39.2	41.6	35.8	34.8
UO - DU	62.3	63.2	54.5	62	55.8	57.4
UP - DU	50	29.9	18.9	39.3	30	17

Table 4: Percentage of subjects who choose A for each binary comparison function of their preferences towards risk and ambiguity.

on the Probability (UP), 59.3% of the risk-averse subjects choose A (and then 40.7% choose B). Our conclusion at the end of Table 2 was that subjects always try to avoid uncertainty on the probability, regardless of the binary choices analyzed. Table 4 makes it possible to complete this conclusion by adding "regardless of the preferences". Indeed, we can observe that the majority of the subjects choose Risk rather than Uncertainty on the Probability, regardless of their preferences towards risk and ambiguity.

The category of preferences seems to have no effect on the binary comparisons R-UP, UO-UP and UO-DU. However, this table allows us to observe that UO is preferred to R only for risk lovers and ambiguity lovers; otherwise, the subjects are indifferent. Concerning the comparison UP-DU, the more an individual is averse, the less DU > UP. Risk-averse subjects are indifferent between UP and DU.

4.2 Robustness of the results

In this section, we present the results of the robustness Task 1-B, and we look to see if these results confirm the ones presented in the previous section.

Recall that Urn B characterizing an uncertain situation is initially imposed on the decision-makers. They are then asked about their willingness-to-pay to move from this uncertain situation to another situation, either risky or uncertain too: Urn A. A decision-maker who wishes to change from Urn B to Urn A has to incur a cost (between €1 and €5). This is the price to pay of the BDM's mechanism for this switch. Thus, such a decision is costly for the decision-maker.

Table 5 presents the percentage of subjects as a function of their WTP (from €0 to €5) that go from Urn B to Urn A for each binary choice. In addition, the last column indicates the average WTP in € for each binary choice.[5]

[5]Appendix C and D provide additional results. Appendix C presents the distribution of the WTPs

For example, for the first binary comparison between Risk and Uncertainty on the Probability, 41.1% of the subjects indicate a null WTP, meaning that they prefer to keep Urn B (here representing Uncertainty on the Probability) rather than to switch to Urn A (here representing Risk), while 58.9% of the subjects have a positive WTP to play with Urn A rather than Urn B (5.3% with WTP=€1, 17.2% with WTP=€2, 18.2% with WTP=€3, 5.3% with WTP=€4, 12.9% with WTP=€5). The average WTP for this binary comparison is €1.80.

	WTP (€)						Average WTP (€)
	0	1	2	3	4	5	
R - UP	41.1	5.3	17.2	18.2	5.3	12.9	1.80
R - UO	66.5	6.7	7.2	10	3.8	5.7	0.95
R - DU	38.8	6.7	16.7	16.7	7.7	13.4	1.88
UP - UO	71.8	8.6	6.7	4.8	2.9	5.3	0.74
UO - DU	42.5	10	15.3	15.3	7.2	9.6	1.63
UP - DU	71.3	4.8	10	7.2	0.5	6.2	0.79
UO - UP	38.8	7.2	19.1	15.3	6.2	13.4	1.83

Table 5: Distribution in % of the WTPs to go from one context to another one for each binary comparison.

Several comments can be made on the basis of Table 5.

First, a majority of the subjects are willing to pay to avoid uncertainty on the probability and play with risk (58.9% of the subjects) and to avoid double uncertainty and play with risk (61.24% of the subjects), whereas they are not to willing to pay to avoid uncertainty on the outcome (and play with risk) since only 33.5% of the subjects have a positive WTP. These results are perfectly in line with those presented in the previous section except for the comparison between risk and uncertainty on the outcome, where they are indifferent in Task 1-A, whereas, here in Task 1-B, they prefer uncertainty on the outcome to risk. These results are coherent since subjects now have to pay to obtain information, and consequently prefer to not switch and stay in a context of uncertainty on the outcome.

Second, the subjects are not willing to pay to avoid uncertainty on the outcome to play with uncertainty on the probability (only 28.3% of the subjects want to switch with a very low average WTP: €0.16). Again, this result confirms the previous one where the subjects prefer uncertainty on the outcome rather than uncertainty on the probability.

Finally, with this additional task, we almost completely validate the ranking obtained between the different uncertain situations, thus validating the robustness of our results.

to go from one context to another one for each binary comparison and each probability level whereas Appendix D proposes to separate the last column of Table 5 depending on the preferences towards risk and ambiguity.

4.3 A sensitivity analysis on the probability level

Up until now, we have presented the results of the experiment for a probability level of 0.5. However, the experiment was carried out with three different levels of probability: 0.1, 0.5 and 0.8. In Task 1, the composition of the urn changes as a function of this probability as follows: 10 balls of the winning color and 90 balls of the other color for a probability of 0.1, and 80 balls of the winning color and 20 balls of the other color for a probability of 0.8. We present here the results for these three levels of probability. The question is: Are the results sensitive to the level of the probability? Table 6 helps us to answer this question. It presents the number of A and B choices in Task 1 for probabilities 0.1, 0.5 and 0.8, and for each binary choice.

	Probability level					
	p = 0.1		p = 0.5		p = 0.8	
	% A	% B	% A	% B	% A	% B
R - UP	2.9	97.1	80.4	19.6	97.6	2.4
R - UO	38.3	61.7	52.2	47.8	48.8	51.2
R - DU	4.3	95.7	69.4	30.6	95.2	4.8
UP - UO	91.4	8.6	21.1	78.9	3.8	96.2
UO - DU	4.3	95.7	78	22	97.1	2.9
UP - DU	No. A = 32.5%; No. B = 67.5%					
Order of preferences	DU > UP > UO > R		R ∼ UO > DU > UP			

Table 6: Percentage of subjects who choose A and B choices for each binary comparison and each probability level.

The trend observed for a medium probability remains valid but is stressed for a high probability, whereas the trend clearly reverses for a low probability level. For medium and high probability levels, the subjects prefer risk to uncertainty on the probability and double uncertainty, and are indifferent between risk and uncertainty on the outcome: R $\sim$ UO $>$ DU $>$ UP. For a low probability level, this trend is different: the subjects prefer all types of uncertainty rather than risk. More precisely, when the probability is low, the order of preferences is: DU $>$ UP $>$ UO $>$ R. This means that subjects behave differently when the probability of winning is low compared to medium or high. In particular, the subjects seem to be "more playful" when the probability of winning is low.

One of the major conclusion of Eliaz and Ortoleva (2015) is that no uncertainty is preferred to uncertainty on any single dimension and to uncertainty on multiple dimensions. Our experiment confirms the conclusion of Eliaz and Ortoleva (2015) for medium and high probability levels concerning the uncertainty on the probability and the double uncertainty. However, we show that subjects are indifferent between risk and uncertainty on the outcome for medium and high probability levels. In addition, we show that when the probability is low, all types of uncertainty are preferred to risk, invalidating the results of Eliaz and Ortoleva (2015).

This trend to reverse preferences when the probability is low is confirmed by the results in terms of WTP in Task 1-B (see Appendix D). These results indicate that the ranking between the different situations strongly depends on the considered probability level. It will then be necessary to systematically consider this level when analyzing the choices of decision-makers under uncertainty.

We deepen the analysis by carrying out mean test comparisons for paired samples for each binary comparison between the average number of B choices for a probability level of 0.5 and the average number of B choices for the other probability levels, 0.1 and 0.8. The results are presented in Table 7. For example, for R-UP, the average number of B choices is 0.20 (for p = 0.5), 0.97 (for p = 0.1) and 0.02 (for p = 0.8). We use t test to compare paired samples 0.20 and 0.97 (average difference of -0.775) and then 0.20 and 0.02 (average difference of 0.172). We repeat these paired comparisons for each binary choice: R-UP, R-UO, R-DU, UP-UO and UO-DU.

	Average No. of B choices		Average difference	Std Error	t	Sig.
R-UP 0.5 / R-UP 0.1	0.2	0.97	-0.775	0.419	-26.776***	<0.001
R-UP 0.5 / R-UP 0.8	0.2	0.02	0.172	0.426	5.841***	<0.001
R-UO 0.5 / R-UO 0.1	0.48	0.62	-0.139	0.550	-3.646***	<0.001
R-UO 0.5 / R-UO 0.8	0.48	0.51	-0.033	0.541	-0.896	0.186
R-DU 0.5 / R-DU 0.1	0.31	0.96	-0.651	0.488	-19.283***	<0.001
R-DU 0.5 / R-DU 0.8	0.31	0.05	0.258	0.491	7.615***	<0.001
UP-UO 0.5 / UP-UO 0.1	0.79	0.09	0.703	0.498	20.414***	<0.001
UP-UO 0.5 / UP-UO 0.8	0.79	0.96	-0.172	0.437	-5.693***	<0.001
UO-DU 0.5 / UO-DU 0.1	0.22	0.96	-0.737	0.463	-23.023***	<0.001
UO-DU 0.5 / UO-DU 0.8	0.22	0.03	0.191	0.418	6.619***	<0.001

*** for significance at 1%.

Table 7: Mean test comparisons for paired samples for each binary comparison.

All the tests are significant, except the one comparing R-UO with probability levels of 0.5 and 0.8. Globally, reducing the probability level (from 0.5 to 0.1) significantly raises the average number of B choices, whereas increasing the probability level (from

0.5 to 0.8) significantly decreases the average number of B choices. This means that the probability level is important and impacts the subject's choices. This additional analysis confirms the previous result that the level of probability has a significant effect on the decision-maker's choice: the higher the probability is, the more likely the decision-maker will opt for a risky situation.

4.4 Link between choices and preferences towards risk and ambiguity

Up until now, we have tackled the two parts of the experiment separately. However, to test Hypothesis 3, we now have to see if individuals' preferences towards risk and ambiguity elicited in Task 2 have an impact (or not) on the decisions taken during the binary choices of Task 1-A. The following table presents the results of a binary Logit regression on the B choices (uncertain contexts) for each binary comparison.

We integrate some socio-demographic variables concerning the participants that we collected at the end of the experiment into the regressions: *Age*, *Gender* and if their university discipline is economics / management (variable *Eco/Manag*). We also consider the level of the probability (0.1, 0.5 and 0.8) and the fact that the results for these variables (*Proba 0.1* and *Proba 0.8*) must be interpreted as a function of what happens with a medium probability level of 0.5. We introduce the variables concerning the preferences towards risk (*Risk pref*) and towards ambiguity (*Amb pref*) through a categorical variable where 0 = aversion, 1 = neutrality and 2 = loving.

	R-UP	**R-UO**	**R-DU**	**UP-UO**	**UO-DU**	**UP-DU**
Constant	-2.352**	-3.013***	-1.891**	0.509	-1.337	-1.260
	(1.069)	(0.806)	(0.950)	(0.996)	(1.100)	(0.835)
Proba 0.1	5.069***	0.607***	4.086***	-3.774***	4.520***	0.000
	(0.461)	(0.206)	(0.384)	(0.309)	(0.394)	(0.219)
Proba 0.8	-2.337***	0.145	-2.250***	1.920***	-2.299***	0.000
	(0.488)	(0.204)	(0.363)	(0.400)	(0.450)	(0.219)
Risk pref.	-0.232	0.149	0.300*	-0.140	0.456**	0.625***
	(0.200)	(0.109)	(0.171)	(0.172)	(0.193)	(0.118)
Amb. pref.	0.507***	0.541***	0.436***	0.415**	0.204	0.298**
	(0.200)	(0.115)	(0.170)	(0.182)	(0.186)	(0.126)
Age	0.037	0.112***	0.007	0.033	-0.025	0.053
	(0.047)	(0.036)	(0.042)	(0.045)	(0.049)	(0.038)
Gender	0.257	0.224	0.527**	-0.033	0.063	0.004
	(0.303)	(0.164)	(0.257)	(0.256)	(0.280)	(0.174)
Eco/Manag	-0.365	-0.225	0.031	0.103	-0.262	0.295
	(0.336)	(0.180)	(0.276)	(0.283)	(0.309)	(0.196)
Log Likelihood	300.276	809.756	395.534	398.713	338.501	731.236

Standard error in parentheses.
The significance levels are computed with a Wald test: *** for significance at 1%, ** at 5% and * at 10%.

Table 8: Logit regression for each binary comparison (N = 627).

On the one hand, we can observe that ambiguity preferences are determinant to explain all the binary comparisons, except UO-DU. Indeed, the ambiguity preferences always have a significant and positive impact on the decision to choose B. This means that as the ambiguity loving increases, the subjects prefer the B option. In particular, for the comparison implying risk (R-UP, R-UO, R-DU), this means that as subjects become ambiguity loving, they prefer the uncertain option rather than the risky one. This result is in line with Aggarwal and Mohanty (2021) who report that ambiguity aversion influences individuals' choices under uncertainty.

On the other hand, the results reveal that risk preferences are significant only for the comparisons implying Double Uncertainty (R-DU, UO-DU, UP-DU). More specifically, as risk loving increases, subjects prefer DU rather than Risk, Uncertainty on the Outcome or Uncertainty on the Probability.

The level of the probability also seems to be determinant. A probability level of 0.1 often has (except for UP-UO where the impact is negative, and UP-DU where it is not significant) a significant and positive impact compared to a probability level of 0.5 on the B choice. A probability level of 0.8 acts like a significant disincentive to choose uncertainty on the probability (rather than risk), double uncertainty (rather than risk and uncertainty on the outcome), but has a positive and significant effect on the choice of uncertainty on the outcome rather than uncertainty on the probability, and a positive but not significant impact on the choice of uncertainty on the outcome rather than risk. These results corroborate the ones already established in the previous section: for low probability, subjects seem to be "playful" and prefer uncertainty to risk, and this trend reverses as the probability level increases.

Sometimes other variables appear to be significant, like *Age* with a significant effect on the choice of UO rather than R, or *Gender* with a significant and positive effect on the choice of DU rather than R. The variable *Eco/Manag* is never significant. It has often been shown that age can be a factor in explaining the level of risk aversion, as well as the choices made in uncertain situations. In our experiment, we only highlight the significant effect of age on the comparison of risk and uncertainty on the outcome. Such a result confirms the fact that decision-makers do not behave in the same way in a situation of uncertainty on the probability, or on the outcome, or on both. Similarly, gender is often an explanatory factor of preferences as well as of choices (Jianakoplos and Bernasek, 1999; Eckel and Grossman, 2008). We partially validate this finding here, indicating that gender can significantly influence decisions in a situation of double uncertainty. Gender and age seem to be two key factors that can explain decisions under uncertainty.

4.5 Testing hypotheses

In this section, we compare the research hypotheses formulated in Section 2 with the results obtained.

First, the results of Table 6 indicate that, for medium and high probability levels, the subjects always prefer risk to uncertainty on the probability and double uncertainty, whereas they seem to be indifferent between risk and uncertainty on the outcome (except the risk and ambiguity lovers who preferred UO to R, as presented in Table 4). The robustness check provided by Task 1-B is mostly in accordance with this result. All in all, Hypothesis 1 is only partially validated for medium and high probability levels since, contrary to what we thought, individuals do not prefer risk to uncertainty on the outcome. Considering the level of the probability changes the results. Indeed, Hypothesis 1 is never validated for a low probability level, since the result of Table 6 indicates a preference for uncertainty, regardless of the source, rather than for risk.

Second, our results clearly show that the subjects do not equally consider uncertainty on the probability and uncertainty on the outcome, regardless of the level of the probability, so that Hypothesis 2 is confirmed. More precisely, for medium and high probability levels, we show that subjects prefer facing uncertainty on the outcome rather than uncertainty on the probability (Task 1-A, Table 2). The robustness check provided by Task 1-B confirmed this result since more than 70% of the subjects indicated a null WTP, meaning that they prefer to play with uncertainty on the outcome rather than uncertainty on the probability (Task 1-B, Table 5). However, for low probability levels, the reverse occurs (Table 6): subjects prefer uncertainty on the probability rather than uncertainty on the outcome. We then contribute to the literature with this new result: individuals prefer uncertainty on the probability rather than uncertainty on the outcome when the probability level is low, whereas the opposite is true for medium and high probability levels.

Third, the results of the MPL elicitation procedure show that the subjects are, on average, risk-neutral and uncertainty-averse (Table 3). The analysis of the distribution of the switching points reveals important differences between risk and uncertainty. Indeed, under risk, the subjects are equally distributed between the three classes of preferences (loving, neutral, averse), whereas under ambiguity, approximately 60% of the sample is ambiguity-averse. In addition, we show that ambiguity preferences have a significant effect on the decision-maker's behavior under all sources of uncertainty. More precisely, the greater the ambiguity loving is, the greater the preference of the subjects for the uncertain options (rather than the risky one) will be, regardless of the source of uncertainty (on the probability, on the outcome, or on both). Finally, we show that risk preferences also have a significant effect on the decision-maker's behavior, especially when the decision implies double uncertainty. Indeed, as risk loving increases, the subjects prefer the double uncertainty to the other options (risk, uncertainty on the outcome or uncertainty on the probability). All in all, Hypothesis 3 is validated concerning ambiguity preferences, but only partially concerning risk preferences.

5 Discussion and conclusion

This article analyzes the way individuals face different sources of uncertainty. We focus on four contexts: risk, uncertainty on the probability, uncertainty on the outcome and double uncertainty. We compare these four contexts two-by-two in binary choices. We also elicit the individual's preferences towards risk and ambiguity. In a lab experiment with students, we show that: (i) individuals prefer uncertainty, regardless the source, rather than risk for a low probability level; (ii) for medium and high probability levels, subjects prefer facing uncertainty on the outcome rather than uncertainty on the probability, whereas the opposite occurs for a low probability level; (iii) ambiguity preferences have a significant effect on the individual's behavior under all sources of uncertainty, whereas risk preferences have an impact only for comparisons implying double uncertainty. These results allow us to partially validate most of the research hypotheses formulated from the existing literature. In particular, our experiment contributes precision to the role of the probability level on an individuals' decision under risk and uncertainty. We also highlight the need to consider, in addition to risk and ambiguity, the uncertainty on the outcome.

The questions raised in this article are not without consequences. They imply issues concerning the orientation of efforts (and, subsequently, the public funds necessary, the prioritization of investments, etc.) to improve knowledge and information that will make it possible to make relevant decisions. More precisely, our results reveal that individuals prefer facing uncertainty on the outcome rather than uncertainty on the probability for medium and high probability levels, whereas the opposite is true for a low probability level. This means that, depending on the probability level, public efforts to reduce uncertainty should be make either on the uncertainty on the outcome or on the uncertainty on the probability. If we take the examples from the introduction dealing with natural hazards in agriculture or forestry, we can assume that the probability level is low. Indeed, such events are commonly characterized as low-probability, high-consequence events. In that case, public efforts should attempt to reduce uncertainty on the probability rather than uncertainty on the outcome.

The topic addressed in this article raises the question of the representation of uncertainty on the outcome in the form of an experiment. Indeed, in this article, we consider all sources of uncertainty: on the probability, on the outcome, and on both. The uncertainty on the probability is often studied and is represented in the form of an already well-established experiment: the unknown distribution of colored balls in an urn. However, uncertainty on the outcome is rarely analyzed and, consequently, the way to represent it in an experiment is not as widely accepted. In this article, we explore a way similar to the one proposed by Eliaz and Ortoleva (2015). We assume that if a ball of the winning color is drawn from the urn, then the subject wins an amount between €0 and €40 (with the sure outcome of €20 representing the center of the interval); otherwise, €0. Our results may be influenced by the value that we consider for the upper bound, *i.e.*, €40. Further research is required to further analyze this question and, more generally, to propose alternative ways of representing uncertainty on the outcome in an experiment.

A Screenshot of the drop-down menu

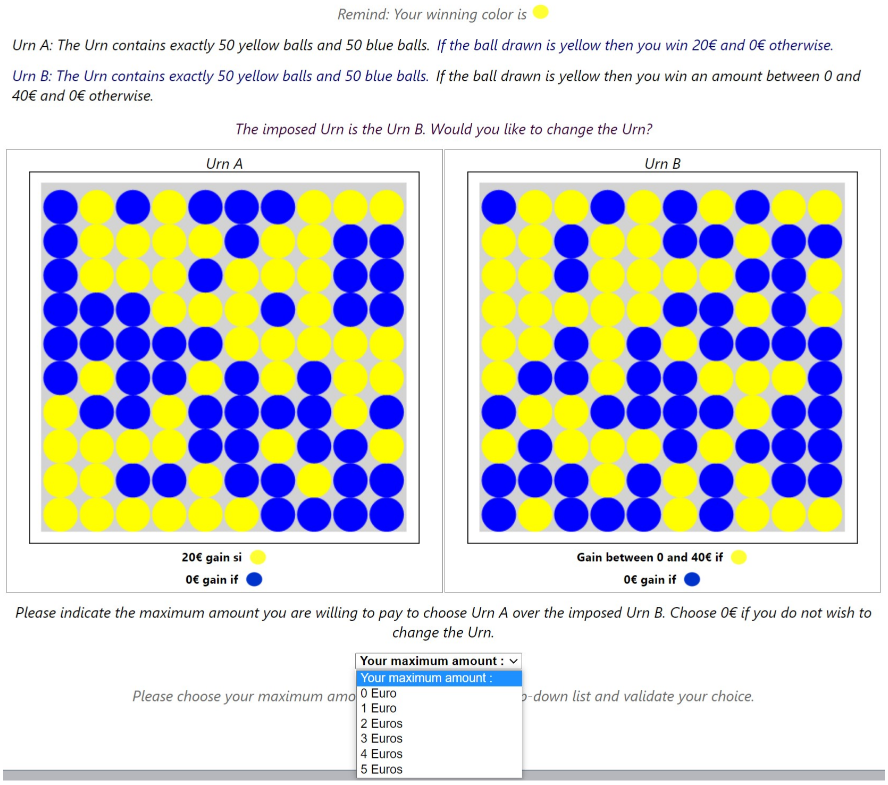

Figure 5: The WTP to go from Urn B (UO) to Urn A (R) for a winning color yellow and a probability of 0.5.

B An analysis of the inconsistent choices

In this appendix, we propose to analyze the potential inconsistency of some subjects. We consider as inconsistent, subjects whose preferences are not transitive, meaning that their choices do not allow to obtain a final ranking of each possible option as regards to the others.

Let's take an example. Recall that for each probability level (10%, 50%, 80%), the subjects take 5 decisions : R vs. UP, R vs UO, R vs. DU, UP vs. UO, UO vs. DU and one additional decision is taken for UP vs. DU.

Consider that for these 6 binary choices, a subject indicates the following sequence: UP>R (UP prefers to R), R>UO, DU>R, UO>UP, UO>DU and UP>DU. These choices are not transitive and do not allow to obtain a final ranking. We assume that the subject is inconsistent.

Consider that for these 6 binary choices, a subject indicates the following sequence: R>UP, UO>R, R>DU, UO>UP, UO>DU, DU>UP. These choices are transitive and allow to obtain the following final ranking : UO>R>DU>UP. We assume that the subject is consistent.

We obtain that the subject's inconsistency is probability-dependent as indicated in the following table :

	p = 10%	p = 50%	p = 80%	No. of decisions
Inconsistent	13	56	12	81
Consistent	196	153	197	546

Table 9: Number of consistent and inconsistent subjects for each probability level.

This means that among the 209 subjects of our sample, approximately 6% are inconsistent when the probability level is either low or high, whereas the percentage goes up to 27% for medium probability level. At the macro level, this result indicates that approximately 12% of the decisions taken are inconsistent.

We go deeper and try to identify some explaining variables to this inconsistency through a simple linear regression. The main variable is binary : inconsistent = 0 (N=81), consistent = 1 (N=546). We obtain the following results:

	Coefficients non standardized		Coefficients standardized		
Model	B	Std Error	Beta	t	Sig.
Constant	0.748	0.101		7.388	<0.001
Proba 0.1	0.206	0.031	0.289	6.648	<0.001
Proba 0.8	0.211	0.031	0.296	6.803	<0.001
Risk pref.	0.036	0.017	0.089	2.181	0.030
Amb. Pref.	-0.068	0.017	-0.168	-3.966	<0.001
Age	-0.001	0.005	-0.012	-0.292	0.770
Gender	-0.073	0.025	-0.114	-2.880	0.004
Univ_degree	-0.061	0.027	-0.093	- 2.254	0.025
Eco / Manag.	0.034	0.027	0.048	1.239	0.216
Income	0.000	0.013	0.001	0.024	0.981
Expe Payment	0.003	0.001	0.083	2.152	0.032

Dependent variable : consistent = 1

Table 10: Linear regression to explain the consistency *(Adjusted R^2 = 0.112).*

This regression proves the significant impact of the probability level on the subject's consistency. A probability level of 10% or 80% has a significant and positive impact on the consistency as compared to a level of 50%. This means that a higher level of inconsistency appears with a medium probability level. Individuals seem to have difficulties to apprehend such a medium probability level as compared to more contrasted ones, like

10% and 80%. Other variables appear significant:

• The higher the risk aversion is, the lower the inconsistency will be (*Risk pref.*).
Individuals with a strong risk loving tend to be more careful and precise in their choices and therefore consistent in their decision-making.

• The higher the ambiguity loving is, the higher the inconsistency will be (*Amb. pref.*).
Individuals who like ambiguity may tend to respond a little too hastily and quickly, and so favor choices where they feel that ambiguity is strongly present, and it is often admitted that hasty choices can lead to inconsistent choices.

• Being a woman increases significantly the inconsistency (*Gender*).
The gender is found to be significant in lots of other decisions implying risk or uncertainty. For example women are found to be more risk averse than men in general (Jianakoplos and Bernasek, 1999).

• The higher the university degree is, the higher the inconsistency will be (*Univ_ degree*).
This means that having higher cognitive abilities does not prevent inconsistency.

• The higher the subject's payment received during the experiment is, the lower the inconsistency will be (*Expe Payment*).
This result seems to suggest that subjects who are particularly interested by the payment take more care to their answers and this increases the consistency.

C Distribution of the WTPs

	p = 0.1		Average	p = 0.5		Average	p = 0.8		Average
	WTP = 0	WTP > 0	WTP in €	WTP = 0	WTP > 0	WTP in €	WTP = 0	WTP > 0	WTP in €
R - UP	90	10	0.25	41.1	58.9	1.80	6.2	93.8	4.00
R - UO	76.1	23.9	0.69	66.5	33.5	0.95	60.3	39.7	1.16
R - DU	90.4	9.6	0.26	38.8	61.2	1.88	5.7	94.3	3.99
UP - UO	9.6	90.4	3.64	71.8	28.2	0.74	92.8	7.2	0.16
UO -DU	90	10	0.22	42.6	57.4	1.63	7.7	92.3	3.89
UP - DU	71.3	28.7	0.79	71.3	28.7	0.79	71.3	28.7	0.79
UO - UP	89.5	10.5	0.31	38.8	61.2	1.83	7.2	92.8	3.87

Table 11: Distribution in % of the WTPs to go from one context to another one for each binary comparison and each probability level.

D Table 5 as a function of the categories of preferences towards risk and ambiguity

The last column of Table 5 may be broken down depending on preferences towards risk and ambiguity as follows:

	Risk			Ambiguity		
	Averse	Neutral	Loving	Averse	Neutral	Loving
R - UP	2.03	1.88	1.82	2.19	1.50	1.50
R - UO	1.40	0.84	1.31	1.17	1.64	1.11
R - DU	2.10	1.76	1.71	2.05	1.79	1.43
UP - UO	1.07	0.52	0.76	0.95	0.64	0.54
UO - DU	1.50	1.72	2.00	1.93	1.21	1.75
UP - DU	1.13	0.68	0.84	0.93	1.29	0.61
UO - UP	1.13	1.68	2.09	1.57	1.50	2.07

Table 12: Average WTP (in €) in the various contexts.

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